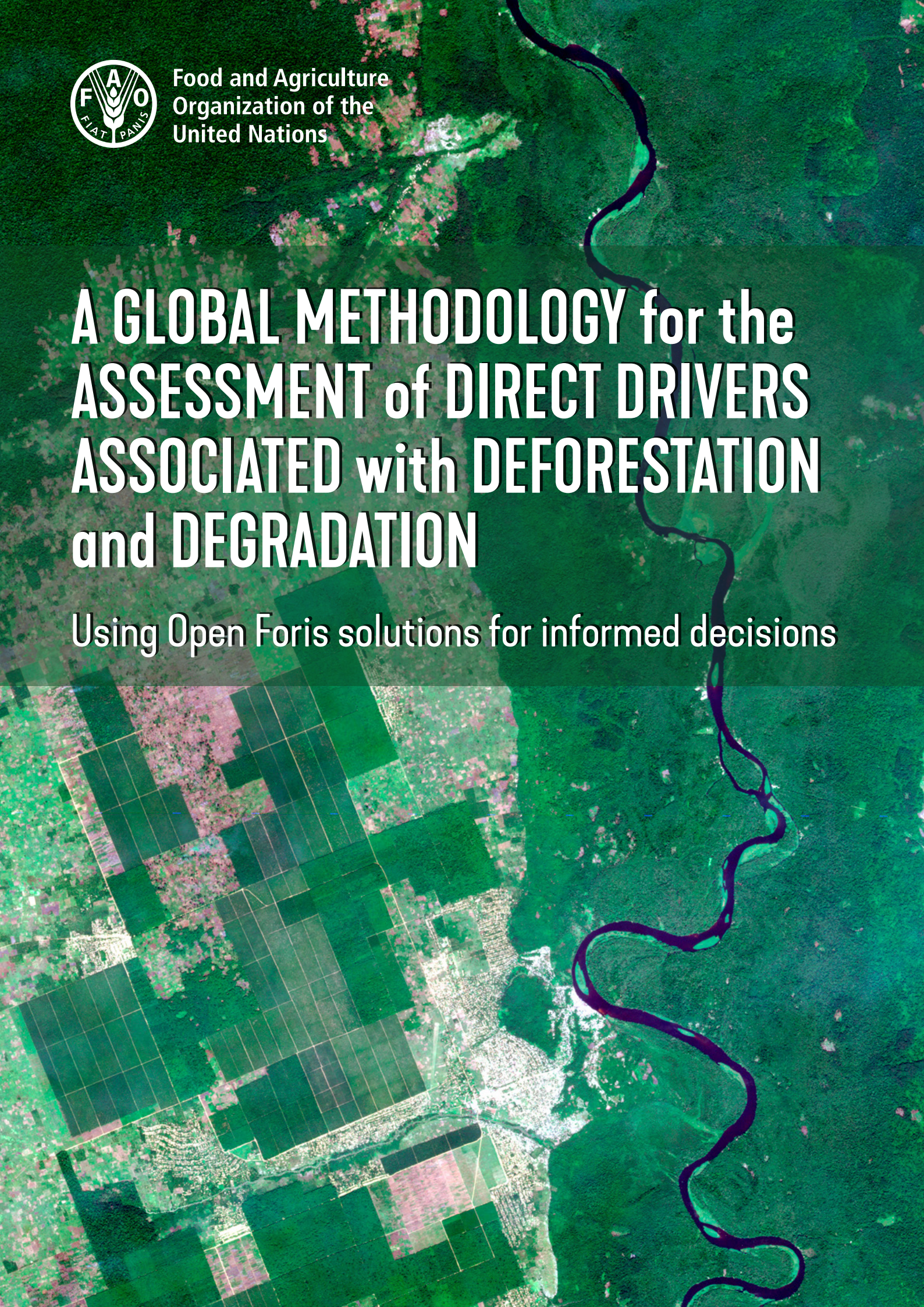

Food and Agriculture Organization of the United Nations

A GLOBAL METHODOLOGY for the ASSESSMENT of DIRECT DRIVERS ASSOCIATED with DEFORESTATION and DEGRADATION

Using Open Foris solutions for informed decisions

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A GLOBAL METHODOLOGY for the ASSESSMENT of DIRECT DRIVERS ASSOCIATED with DEFORESTATION and DEGRADATION

Using Open Foris solutions for informed decisions

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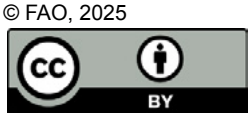

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Contents

Contributors vi

Acknowledgements viii

Foreword ix

Abbreviations x

Executive summary xi

Introduction 1

Objectives 2

Methods 18

Results from Central Africa 29

Assessing direct drivers of forest disturbance in Central Africa 46

Conclusions 53

References 54

Figures

1. Proximate causes of forest decline 3

2. Main Congo Basin country drivers identified and their relative weights 5

3. Example of deforestation 11

4. Example of degradation 11

5. The study area covering six countries of Central Africa 13

6. Overview of the Open Foris Solutions 18

7. Methodological approach 19

8. Overview of the available archive satellite data 20

9. Cloud-free data coverage for Landsat 8 and Sentinel-2, 2015 21

10. Available data coverage of Sentinel-1 and ALOS PALSAR, 2015 21

11. Percent tree cover for the entire study region 29

12. Area distribution and cumulative percentage of tree cover 30

13. Forest mask for Central Africa 30

14. Forest fragmentation map for the baseline year, 2015 31

15. Vegetation and land cover for the Central African study region with relative size of classes, 2015 32

16. Total area of each forest type, the distribution of fragmentation classes and average above ground biomass 33

17. Summary of Collect Earth Online validation data showing forest class, type of change and date of change 34

18. The distribution of stable and non-forest types in the visually interpreted dataset 35

19. Annual distribution of deforestation and degradation by forest type 36

20. Annual change by fragmentation class 37

21. Cumulative proportion of deforestation and degradation relative to distance to nearest road or settlement 38

22. Diagram representing the overlap and frequency of observed drivers 39

23. Grouped drivers, 2015–2020 41

24. Presence of driver archetypes in different forest fragmentation classes 41

25. Household perspectives 42

26. Average land area used by households in all villages surveyed 42

27. Distance to forest cleared by village 43

28. Mock-up of Geo4LUP landing page in SEPAL 44

29. Inputs and output schematic for Geo4LUP, and a sample output 45

B1.1 Synthesis of key charcoal-deforestation dynamics findings from the literature relevant for the Congo Basin urban areas that form loci of urban charcoal demand across Central Africa. Blue circles are approximate radius of supply..... 48

30. Cropland expansion in the six countries of the study region 51

Tables

1. Overview of studies on drivers at global, regional and national levels 6
2. Forest definitions used on national, regional and global scales 9
3. Operational project definitions of deforestation and degradation 11
4. Driver definitions and characteristics 14
5. REDD+ activity matrix describing forest transitions 16
6. Review of available satellite data sources for monitoring deforestation and degradation 20
7. Regional classification system 22
8. Forest fragmentation classes 24
9. An overview of change detection approaches 25
10. Four interrelated data collection modules used for local-level socioeconomic analysis of proximate and underlying drivers of forest change in Central Africa 28
11. List of composite products 29
12. Accuracy assessment of forest/non-forest map 31
13. Adjusted forest and non-forest area (area adjusted) 31
14. Observed combinations of drivers were grouped into thematic classes or archetypes 40

Boxes

1. Charcoal production as a driver of deforestation and degradation in the Congo Basin 48

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Foreword

Forests cover nearly one-third of the Earth's land surface, providing abundant ecosystem services such as clean water and climate mitigation; they are home to biodiversity and livelihood sustaining resources for millions of people. However, forests remain under constant pressure from anthropogenic direct drivers of change, including conversion to agriculture, timber exploitation, infrastructure development and resource extraction.

In order to reduce pressures on forest and directly address these threats, accurate, detailed and timely information is needed to provide governments, international agencies and civil society with the capacity to monitor forest change and understand associated drivers. Innovative solutions and technologies derived from remote sensing satellites – developed by the Food and Agriculture Organization of the United Nations (FAO) and partners – have contributed to the empowerment of the collection, analysis and understanding of forest ecosystems.

This report synthesizes more than 20 months of effort to produce a state-of-the-art approach to monitoring deforestation, degradation and quantifying associated direct drivers. Collaborative efforts were made between: FAO staff in partner countries in Central and West Africa, local forestry experts from government ministries, scientists from international research centres, specialists in academia and non-governmental organizations.

The document evaluates recent literature and available research and describes the various approaches and solutions to monitoring forests and drivers, producing a synthetic global approach using Open Foris solutions, including Collect Earth Online and the System for Earth Observation Data Access, Processing and Analysis for Land Monitoring (SEPAL). This global methodology is a replicable and transferable approach to assessing forest cover change and associated drivers in space and time. It has already been replicated in the Economic Community of West African States (ECOWAS) region.

This publication serves to allow anyone, anywhere to comprehend the specific drivers of forest change and address them through mitigation and targeted efforts to meet the ambitious global objectives of halting deforestation and degradation by 2030.

Zhimin Wu

Director, FAO Forestry Division

Abbreviations

ALOS PALSAR	Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar
BFAST	Breaks for Additive Seasonal and Trend
CAFI	Central African Forest Initiative
CEO	Collect Earth Online
ESRI	Environmental Systems Research Institute
FAO	Food and Agriculture Organization of the United Nations
GEE	Google Earth Engine
GIS	geographical information systems
MSPA	morphological spatial pattern analysis
REDD+	Reducing Emissions from Deforestation and Forest Degradation, and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries
SEPAL	System for Earth Observation Data Access, Processing and Analysis for Land Monitoring

Units and formulae

CI	confidence interval
ha	hectare(s)
km	kilometre(s)
km^2	square kilometre(s)
m	metre(s)
m^2	square metre(s)
mg	milligram(s)
N	sample size

Executive summary

Despite international efforts and progress towards reducing deforestation and degradation, population growth, demand for natural resources and human dependence on forest ecosystems contribute to forest loss, ultimately impacting global climate and sustainable development efforts. Many studies have proven that small-scale or subsistence agricultural activities are the most prevalent direct driver of forest loss, requiring specific solutions to achieve food security, maintain livelihoods and adapt to future climate changes.

This study uses satellite imagery, analysed with open-source tools from the Open Foris package (most notably the System for Earth Observation Data Access, Processing and Analysis for Land Monitoring [SEPAL]) to identify deforestation, degradation and associated direct drivers in six Central African countries. Dense time series are used to process hundreds of satellite image observations over the 2015–2020 period to automatically observe forest disturbances, which were then validated and associated with specific direct drivers through visual interpretation of high-resolution imagery.

There are several major conclusions from the study:

- **Deforestation and degradation vary by forest type.** Dense forest (the most common forest class, occupying a little over half of all forest area in 2015) only represent a third of all observed forest disturbances. Deforestation and degradation are more likely to occur in dry open and secondary forests.
- **More than half of all disturbances are occurring in already fragmented forests, rather than intact core ecosystems.** More specifically, these changes are occurring in corridor forests, which represent one-third of all forests and connect smaller patches of forests. Although these forest types have lower biomass than other forest classes, corridors are important for maintaining biodiversity through connectivity.
- **Small-scale agriculture is the major driver of change, and most often present with roads, villages and artisanal forestry, characteristic of the "rural complex".** The contribution of the rural complex to disturbances is relatively stable over time, while artisanal forestry, human infrastructure and agriculture associated with infrastructure are increasing. This contextual and geospatial information on drivers in time and space can inform the impact of existing interventions, while helping target future activities and support sustainable development while addressing local livelihoods and need, food security, and associated underlying drivers.

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Introduction

Tropical forests are a globally important carbon sink, playing a crucial role in: mitigating anthropogenic climate change (Harris *et al.*, 2021; Houghton, 2005; Justice *et al.*, 2001; Mitchard, 2018); supporting the livelihoods of millions of local people (Eba'a Atyi *et al.*, 2022; Oldekop *et al.*, 2020); and providing habitat to a large proportion of the world's valuable terrestrial biodiversity (Liang *et al.*, 2016). The benefits provided by intact tropical forests that are relatively free from human influence and disturbance are potentially even greater (Maxwell *et al.*, 2019), and the value of this natural capital is staggering (Costanza *et al.*, 1997; Kappen *et al.*, 2020).

Despite the intrinsic link between healthy forests and human activities and economies, forests continue to be converted to other land uses, and remain under constant threat of disturbance. After fossil fuel combustion, deforestation is the second largest source of global carbon emissions (IPCC, 2014; Le Quéré *et al.*, 2016; Smith *et al.*, 2014; Van der Werf *et al.*, 2009). The emissions associated with degradation, or disturbances within forest areas, are also significant, although mostly unaccounted for or underestimated (Pearson *et al.*, 2017). Additionally, climate change is further threatening the production of forest goods and services, and the relationships between multiple stakeholders who depend on and benefit from forest ecosystems (Bele, Sonwa and Tiani, 2015; Sonwa *et al.*, 2012).

Given the role of forests in sequestering carbon, there have been many coordinated international efforts to mitigate climate change through forest conservation, which include defining deforestation reduction targets and accurate monitoring of deforestation and forest degradation using earth observation data (Gibbs *et al.*, 2007). These datasets provide unprecedented, up-to-date information on various aspects of forest change for global or tropical forests. While there is a great scientific interest in providing wall-to-wall global forest data products and analysis, these data alone are often not sufficient for robust, accurate deforestation estimates and trends (Sandker *et al.*, 2021); they are also often not relevant to decision-making at national or subnational scales. Countries are more likely to use, understand and value data they produce and update themselves, and can apply to national forest monitoring systems for decision-making and implementation of policies.

This report describes a comprehensive methodology to evaluate forest trends and the associated direct drivers using open-source tools provided through the SEPAL platform from FAO[1] and the Open Foris toolkit.[2] The approach is piloted in six countries in Central Africa.

[1] https://sepal.io

[2] https://openforis.org

Objectives

Deforestation and forest degradation are complex processes that have many underlying causes. A comprehensive understanding of forest degradation and conversion to other land uses is instrumental for the development of policies and actions aiming to reduce the loss of forests and its associated carbon emission. It is important to understand recurring patterns and correlations that can help countries tailor their efforts towards reducing forest loss.

The causes of deforestation and forest degradation vary both regionally and temporally (Curtis *et al.*, 2018). Different studies refer to agricultural expansion (cropland and pasture) as the largest direct cause of global deforestation (FAO, 2022a; Gibbs *et al.*, 2010; Hosonuma *et al.*, 2012; Kissinger, Herold and De Sy, 2012; Sandker *et al.*, 2017). Commercial agriculture is estimated to be responsible for around 70–90 percent of worldwide deforestation (FAO, 2022). In Africa, both commercial and subsistence agriculture may account for similar importance in terms of forest loss, while fuelwood collection, charcoal production and livestock grazing (to a lesser extent) in forests are the most important drivers of degradation (Hosonuma *et al.*, 2012; Kissinger, Herold and De Sy, 2012).

However, these studies as well as existing national studies on the drivers of deforestation and forest degradation in the Central African region are generally based on data acquired up to 2014 and do not consider the recent trends in observed tree cover loss (Hansen *et al.*, 2013). They also do not take into account the importance of the spatial fragmentation of forests and the role played by degradation induced by forest exploitation (Molinario, Hansen and Potapov, 2015). Furthermore, they simplify causes of deforestation into a single driver, which does not adequately reflect the complex local context and interacting causes, such as decisions that lead to anthropogenic forest disturbance at local scales (Ferrer Velasco *et al.*, 2020; Bernhard, Shapiro and Hunt, 2024).

These recent trends and the lack of updated studies result in little consensus on the main drivers and agents of forest change at regional scales. There is a pressing need to systematically quantify the direct causes of deforestation and degradation via a systematic and comprehensive approach (Brandt, Nolte and Agrawal, 2016, 2018; Karsenty *et al.*, 2017). An updated assessment should provide validated evidence on the role and weight of different drivers of forest loss and support decision-making to address related challenges. A spatially explicit approach should also facilitate the assessment of the efficiency of policies and actions in different contexts. Improved spatial data on deforestation and forest degradation, and an improved understanding of the drivers, will support land-use planning approaches in two pilot areas where the regional analysis indicated clear opportunity for supporting decision-making and planning related to land use.

In this context, FAO has developed a robust methodology to assess the recent trends and drivers of deforestation and forest degradation via collaborative approaches, in which national experts, research institutes and civil society work together and combine resources and data to reach a common view on the current and future causes and drivers of anthropogenic forest disturbances. These tools generate improved information for decision-making and land-use planning in the relevant management context.

FAO, in partnership with CAFI[3] and a coalition of donor and partner countries have assessed forest dynamics using cloud-computing solutions and open-source tools. The approach maps disturbances (both deforestation and degradation) and quantifies the contribution of multiple associated direct drivers. The methodology is used to assess deforestation and forest degradation trends and their associated current and historical direct drivers in six Central African countries as part of an international effort to mitigate climate change, support the Sustainable Development Goals and protect biodiversity.

This study is a result of the applied methodology assessing forests in the six Central African countries. Despite being such an important resource for the planet, Central Africa is relatively understudied and receives significantly less funding than countries on other continents (Eba'a Atyi *et al.*, 2019; White *et al.*, 2021). New carbon finance opportunities supporting "high forest, low deforestation" (HFLD) countries could help fill some of these gaps when sufficient information is available to target interventions and investments.

The major components of this project include the generation of wall-to-wall geospatial data on forest cover types, changes and discerning areas of deforestation from degradation for the entire Central African region. These products are validated via visual interpretation and the presence of various direct drivers is identified to evaluate the direct causes of disturbance and interpret in the context of strategic investments for climate change mitigation and support for national efforts for emissions reduction.

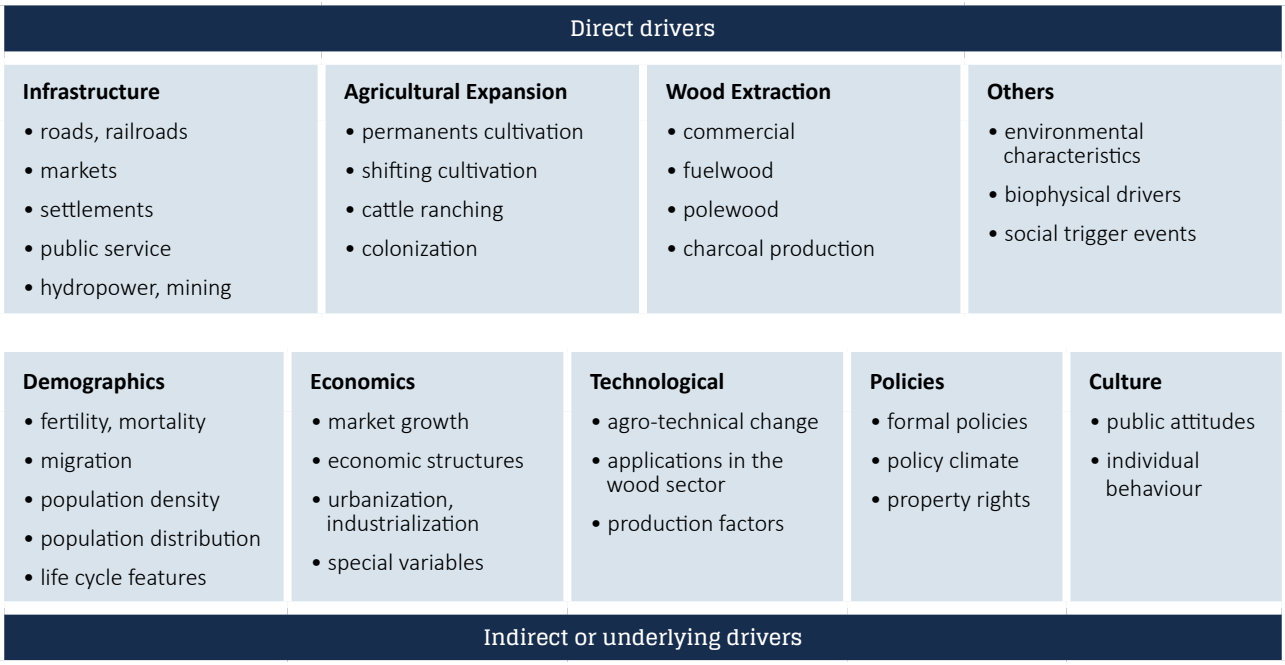
[3] https://www.cafi.org

Direct drivers of forest change

Monitoring forest change and disturbance is one aspect of monitoring relevant to climate change, whereas the understanding of the direct drivers of forest change is critically important for implementing required mitigation efforts and policies. For example, different approaches are necessary to tackle forest impacts associated with activities by large companies or individual smallholders for local subsistence activities (Jayathilake *et al.*, 2021; Minang and Van Noordwijk, 2013; Moonen *et al.*, 2016).

There are many potential threats to Central African forests from various drivers; in this study, we direct our focus to multiple direct drivers (Figure 1) which are detectable through satellite imagery, and are further described in the following subsections.

Figure 1. Proximate causes of forest decline



Source: Geist, H.J. & Lambin, E.F. 2002. Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *BioScience*, 52(2): 143. https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2

Subsistence agriculture

Agriculture is considered to be the most important global driver causing the large majority of forest loss (Kissinger, Herold and De Sy, 2012; Branthomme *et al.*, 2023). The demand for agricultural products is intrinsically linked with population growth, development, and wealth or poverty.

Slash-and-burn approaches, mostly by poor subsistence farmers, is the process of clearing vegetated land, burning the field before establishing agriculture for a few years until yields decline, and leaving the land to fallow (Hauser and Norgrove, 2013; Molinario *et al.*, 2017). In many cases, these activities can cause fires to spread out of controlled areas and into edges of clearings, resulting in even more forest disturbance.

In other cases, areas can either be reused eventually or left to regenerate to become forest again, which could mean becoming more or less carbon neutral (Tinker *et al.*, 1996); however, as populations and demands for more yield increase, more land is cleared or fallow times reduced, resulting in permanent land cover change (Hauser and Norgrove, 2013). In Central Africa, the combination of rural developing areas and associated agricultural exploitation around forests has been named the rural complex, which has expanded over time and is a cultural norm (Mayaux, Richards and Janodet, 1999; Molinario *et al.*, 2017; Molinario, Hansen and Potapov, 2015). Slash and burn is not scalable for large populations; in these situations, agricultural intensification, commercialization or cattle ranching are established, which prevents natural regeneration – as seen in South America (van Vliet *et al.*, 2012). The agricultural frontier and smallholder clearing in Central Africa has been expanding as population and associated demand grows while mechanization, infrastructure, and business climate are limiting great advancements in efficiency or productivity.

Industrial agriculture

Most agricultural activities in Central Africa are subsistence or small-scale; industrial activities are relatively limited. Nevertheless, there is significant potential and political will for increasing industrial production to meet an increasing demand for agricultural products related to increasing population in order to improve food security (Hourticq *et al.*, 2013; Tyukavina *et al.*, 2018). Industrial activities in the region are localized in specific areas of Gabon, in the southwest of Cameroon, and in the southeast of the Democratic Republic of the Congo.

Infrastructure development

Major development corridors are expected to boost agricultural production, exports and local economies. These will include large-scale expansion of infrastructure which could bisect some of the most intact forests in Central Africa and are likely to incur drastic irreversible impacts (Kleinschroth *et al.*, 2019; Laurance *et al.*, 2015, 2017; Mosnier *et al.*, 2014). These infrastructure projects comprise roads, railways and power structures that not only cause forest loss and degradation, but effectively open remote areas to further access and disturbance. The Central African region has relatively low access to electricity, and most households are dependent on locally sourced charcoal for preparing food (Megevand, 2013). The underdeveloped electricity sector is expected to expand infrastructure for power plants, dams and electricity transmission networks in the near future (IEA, 2022).

Linear infrastructure such as roads and power lines that cross natural ecosystems have major ecological effects, including forest fragmentation and associated degradation, as well as impacts on water flow, introduction of chemicals, noise and visual disturbances (Seiler, 2003). Roads are also correlated with increased hunting pressure on African wildlife, which can alter mammal communities who play an important role in seed dispersal, therefore affecting forest regeneration (Osuri *et al.*, 2020).

Forestry

Timber extraction from forests can include industrial activities, which range from clear-cutting to selective harvesting, as well as small-scale, subsistence activities including fuelwood collection, all of which can have implications on carbon emissions and ecosystem health (Hosonuma *et al.*, 2012). Timber extraction and exploitation can cause direct disturbance through harvesting, as well as associated impacts through logging roads, skid trails and infrastructure (Pearson *et al.*, 2014).

Industrial exploitation of processed timber is relatively low in Central Africa, with only a small contribution to the global market; imports of wood exceed imports (Megevand *et al.*, 2013). Of all the Congo Basin countries, the Democratic Republic of the Congo has the lowest timber volume, despite having the most forests (de Wasseige *et al.*, 2012), which is attributed to political instability, lack of access and means of transport (Tchatchou *et al.*, 2015). The impacts on forests are more related to exploitation for national demand, which is profitable at small scales and contributes to local infrastructure development (Lescuyer *et al.*, 2014). Many of these enterprises, however, are unregulated or do not follow sustainable practices or can be illegal, resulting in additional impacts and emissions than planned. The impacts of industrial wood extraction in the Democratic Republic of the Congo are limited by selective logging practices, and mostly related to the development of logging roads and skid trails, which can quickly recover when not used – although they still threaten pristine forests by encouraging access and additional destructive activities (Pearson *et al.*, 2014; Samndong *et al.*, 2018).

In Central African countries, and even more in the Democratic Republic of the Congo, the local population relies primarily on fuelwood and charcoal for cooking, as there is little access to electrical infrastructure. Fuelwood consumption is expected to grow dramatically with the increasing population. The supply chain feeding urban areas is largely unregulated, unsustainable or illegal, and the volume of wood removal from forests is steadily increasing and expanding. While in rural areas, fuelwood collection is primarily focused on dead branches and logs, which has minimal impacts, in areas closer to cities, higher demand is driving significant impacts and wide-reaching effects on forests (Samndong *et al.*, 2018).

Industrial mining and extractive industries

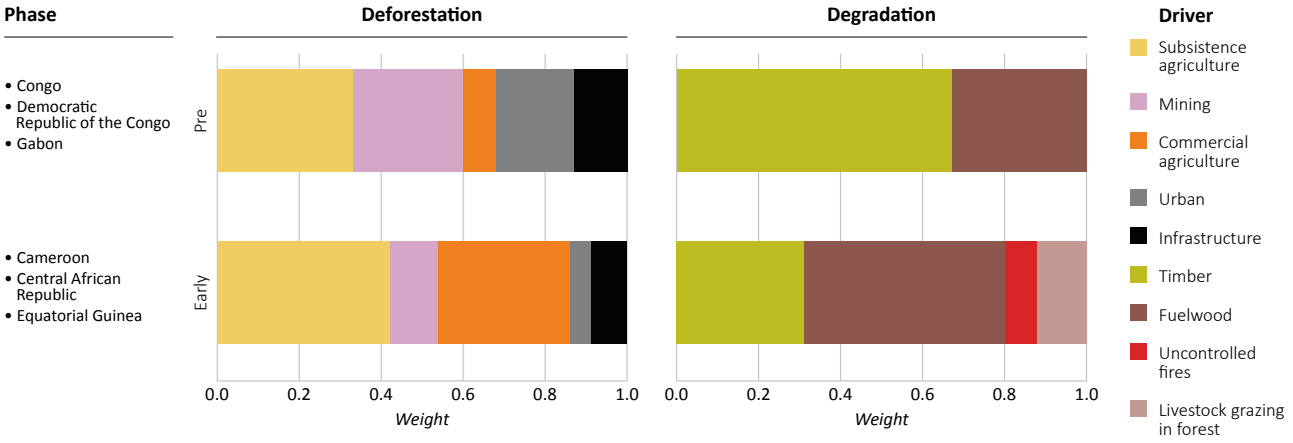
The Central African region hosts a wealth of important mining resources, including valuable cobalt, iron, uranium, bauxite, copper, diamonds and oil (Edwards *et al.*, 2014; Tegegne *et al.*, 2016; Weng *et al.*, 2013). There is an increasing demand in these resources, which increasing prices and profitability are therefore encouraging exploitation as part of the development strategy. This results in overlaps and competing land uses, such as oil development in officially designated protected areas and exploitation, which come at significant social and environmental costs. Industrial mining activities however could result in more stable, secure and beneficial operations than informal small-scale illegal activities (Sovacool, 2019; Stoop, Verpoorten and Van der Windt, 2019). Oil production in the region has mostly been active in Equatorial Guinea and Gabon, and Central African nations have committed to building pipelines to connect resources. This is expected to reduce energy poverty and boost productivity, which could bring further development at the expense of forests. More recently, oil exploration in the heart of the Congo Basin's vast swamp forests has garnered a lot of attention specifically in relation to the vast amounts of carbon which may be released, affecting regional efforts for climate mitigation (Crezee *et al.*, 2022; Maclean and Searcey, 2022).

Assessments of regional drivers

Beyond the specific issue of definitions, deforestation and forest degradation are complex and intricate processes that have many direct and underlying causes (Bustamante *et al.*, 2016; Geist and Lambin, 2001). Agriculture is reported to be responsible for around 70–90 percent of deforestation globally (Kissinger, 2020), which is similar to results from regional studies (Tyukavina *et al.*, 2018). In the review of proposals to the Forest Carbon Partnership Fund (FCPF) (Hosonuma *et al.*, 2012), other factors are driving deforestation in Africa, such as mining, road construction and urban expansion; timber extraction, fuelwood and livestock grazing were identified as the main degradation drivers (Figure 2).

The reference level submissions for national REDD+ programmes[4] evaluate the relative impacts of drivers on forest-related emissions. In the Congo, the reference level submission indicates that most forest-related emissions are from selective logging (Coordination Nationale REDD, 2017). In the Democratic Republic of the Congo, dense forests are mostly converted to agriculture (MEDD, 2018). In Equatorial Guinea, it was found that post-deforestation land use was primarily human settlements, followed by fallow land, pastures and agroforestry (MAGBOMA and FAO, 2020).

Figure 2. Main Central Africa country drivers identified and their relative weights



Note: The phase refers to the forest transition model, where developed countries experienced increased deforestation related to economic development, followed by a period of expanding forest cover. The pre-transition countries have the highest forest cover and lowest rate of loss, while early transition countries have begun the phase of significant forest loss.

Source: Hosonuma, N., Herold, M., De Sy, V., De Fries, R.S., Brockhaus, M., Verchot, L., Angelsen, A. & Romijn, E. 2012. An assessment of deforestation and forest degradation drivers in developing countries. *Environmental Research Letters*, 7(4): 044009. https://doi.org/10.1088/1748-9326/7/4/044009

[4] REDD+ refers to Reducing Emissions from Deforestation and Forest Degradation, and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries.

Several studies have documented the potential of agricultural practices as a driver of deforestation (Carter *et al.*, 2018; Geist and Lambin, 2002; Laurance, Carolina Useche and Rendeiro, 2012), along with reviews of specific information available for the impact of large-scale agricultural plantations in Cameroon, the Congo, the Democratic Republic of the Congo, and Gabon (Feintrenie, 2014). Rainforests were shown to be the primary source for new agricultural land throughout the tropics during the 1980s and 1990s; the majority of the land for agricultural and tree plantation expansion came from forests, woodlands and savannahs – not from previously cleared lands (Gibbs *et al.*, 2010). However, more recent studies indicate increasing cropland conversions in areas that are outside intact forests (Potapov *et al.*, 2022). The majority of global deforestation in the 2000–2010 period appears to be still driven by agricultural expansion (Hosonuma *et al.*, 2012), while charcoal and fuelwood collection drive degradation in Africa (Kissinger, Herold and De Sy, 2012). Many studies conducted in Central Africa have established that subsistence agriculture is the most important driver of deforestation in those countries, while also showing the potential impact of future infrastructure development as a driver of deforestation (Laurance *et al.*, 2015; Tegegne *et al.*, 2016).

Table 1 compiles a selection of studies on the factors of deforestation and degradation in Central Africa.

Table 1. Overview of studies on drivers at global, regional and national levels

Scope	Authors	Date	Title
Global	FAO	2023	How much do large-scale and small-scale farming contribute to global deforestation?
	FAO	2022	The Forest Resources Assessment (FRA) Remote Sensing Survey
	Pendrill *et al.*	2022	Disentangling the numbers behind agriculture-driven tropical deforestation
	Jayathilake *et al.*	2021	Drivers of deforestation and degradation for 28 tropical conservation landscapes
	Sy *et al.*	2019	Tropical deforestation drivers and associated carbon emission factors derived from remote sensing data
	Curtis *et al.*	2018	Classifying drivers of global forest loss
	Mosnier *et al.*	2016	Disentangling the effects of local and global drivers of deforestation with the GLOBIOM model
	Hosonuma *et al.*	2012	An assessment of deforestation and forest degradation drivers in developing countries
	Houghton	2012	Carbon emissions and the drivers of deforestation and forest degradation in the tropics
	Kissinger	2012	Drivers of deforestation and forest degradation: a synthesis report for REDD+ policymakers
	DeFries *et al.*	2010	Deforestation driven by urban population growth and agricultural trade in the twenty-first century
	Rudel *et al.*	2009	Changing drivers of deforestation and new opportunities for conservation
	Rudel	2007	Changing agents of deforestation: from state-initiated to enterprise driven processes, 1970–2000

Scope	Authors	Date	Title
Regional	Tristch *et al.*	2019	Do forest-management plans and forest stewardship council (FSC) certification reduce deforestation in the Congo Basin?
	Tyukavina *et al.*	2018	Congo Basin forest loss dominated by increasing smallholder clearing
	Umunay *et al.*	2019	Selective logging emissions and potential emission reductions from reduced-impact logging in the Congo basin
	Tegegne *et al.*,	2016	Evolution of drivers of deforestation and forest degradation in the Congo Basin forests: exploring possible policy options to address forest loss
	Gillet *et al.*	2016	Quelles sont les causes de la déforestation dans le bassin du Congo? Synthèse bibliographique et études de cas [What are the causes of deforestation in the Congo Basin? Literature review and case studies]
	Tchatchou *et al.*	2015	Deforestation and forest degradation in the Congo Basin: state of knowledge, current causes and perspectives
	de Wasseige *et al.*	2015	Forests of the Congo Basin: forests and climate change
	Megevand *et al.*	2013	Deforestation trends in the Congo Basin: reconciling economic growth and forest protection
	Ernst *et al.*	2013	National forest cover change in Congo Basin: deforestation, reforestation, degradation and regeneration for the years 1990, 2000 and 2005
Cameroon	MINEPDED	2018	Stratégie nationale de réduction des émissions issues de la déforestation et de la dégradation des forêts, gestion durable des forêts, conservation des forêts et augmentation des stocks de carbone [National strategy for the reduction of emissions from deforestation and forest degradation, sustainable management of forests, conservation and carbon stock enhancement]
	Unique, IIASA, and Rainbow	2017	Analyse approfondie des moteurs de la déforestation et la dégradation dans cinq zones agro écologiques [In-depth analysis of the drivers of deforestation and degradation in five agro-ecological zones]
	Dkamela	2011	The context of REDD+ in Cameroon: drivers, agents, institutions
Democratic Republic of the Congo	Molinario *et al.*	2020	Contextualising landscape-scale forest cover loss in the Democratic Republic of Congo between 2000 and 2015
	Butsic *et al.*	2015	Conservation and conflict in the Democratic Republic of the Congo: the impacts of warfare, mining, and protected areas on deforestation
	Ickowitz *et al.*	2015	Agriculture and deforestation in the Democratic Republic of the Congo: a synthesis of the current state of knowledge
	Katembera Ciza *et al.*	2015	Identification des moteurs de déforestation dans la région d'Isangi, République Démocratique du Congo [Identificaiton of drivers of deforestation in the region of Isangi, Democratic Republic of the Congo]
	De Beule *et al.*	2014	Cocoa: Driver of deforestation in the Democratic Republic of the Congo?
	Defourny *et al.*	2011	Analyse quantitative des causes de la déforestation et de la dégradation des forêts en RDC [Quantitative analysis of drivers of deforestation and DRC]
	Shapiro *et al.*	2021	Assessment of proximal drivers of degradation in the DRC, including conflicts, fires, land cover and land use
Equatorial Guinea	MAGBOMA and FAO	2020	Presentación del Nivel de Referencia de Emisiones Forestales de la República de Guinea Ecuatorial a la UNFCC [Submission of the Forest Emissions Reference Level of the Republic of Equatorial Guinea to the UNFCCC]
	MAGBMA and FAO	2018	Estudio de las causas de la deforestación y degradación forestal en Guinea Ecuatorial 2004–2014 [Study of the causes of deforestation and forest degradation in Equatorial Guinea 2004-2014]

Scope	Authors	Date	Title
Congo	Coordination Nationale REDD	2014	Etude de la spatialisation et de la pondération des causes de la déforestation et la dégradation forestière et analyse des options stratégiques, proposées par le R-PP de la République du Congo [Study of the spatialisation and weighting of causes of deforestation and forest degradation and analysis of the strategic options proposed by the R-PP of the Republic of Congo]

Note: Studies can be found in the References section of this publication.

Most studies identify expanding small-scale agriculture as the primary cause of forest loss (Curtis *et al.*, 2018; Tegegne *et al.*, 2016; Tyukavina *et al.*, 2018), while others cite forestry activities as having the greatest impact on forest areas (Justice *et al.*, 2001). It is important to comprehensively assess drivers because not all will have the same impact on carbon stocks, biodiversity (Kissinger, Herold and De Sy, 2012; Shapiro *et al.*, 2021a), or communities (Caradang *et al.*, 2013; Rademaekers *et al.*, 2010).

This study addresses the proximate or direct drivers of deforestation and degradation, defined as the immediate human actions that directly affect forest cover and biomass (Geist and Lambin, 2002; Kissinger, Herold and De Sy, 2012; Meyfroidt, 2016), which is different from post-deforestation land use which can only identify one class of change. It assesses multiple overlapping direct drivers on both deforestation and degradation, as this reflects the realities of local processes, stakeholders and decisions that result in deforestation and degradation (Moonen *et al.*, 2016). The effect of scale is also very important. Many studies have only identified one possible direct driver (Curtis *et al.*, 2018; De Sy *et al.*, 2019; Tyukavina *et al.*, 2018; Bernhard *et al.*, 2023; Oshan *et al.*, 2022), whereas direct drivers are multiple and more significantly correlated to changes in forest cover at smaller scales (Ferrer Velasco *et al.*, 2020), providing contextual information to properly define and focus interventions and mitigations.

Definitions

Definitions of forest

There are more than 1 000 different definitions for forests and wooded areas in use around the world with some countries adopting definitions according to biophysical differences in forest formations, perceptions, objectives (use and management), context, and values (Buettel, Ondei and Brook, 2017; Chazdon *et al.*, 2016; FAO, 2006; Ghazoul and Chazdon, 2017; Lund, 2009, 2014; Putz and Redford, 2009).

Regarding definitions of forests, two main options are available for national scales or larger. The first option consists of assigning one common definition and applying associated thresholds in all biomes and countries to map forest and forest change. In FAO's Global Resource Assessment (FRA), forests are defined as "land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use" (FAO, 2020a, p. 4). It uses a single definition with relatively conservative thresholds in order to include and compare all biomes and countries at the global, continental and biome levels (with the same variable). This approach is valid but presents limitations for assessments at finer scales; it neither reflects all granularity of national circumstances nor aligns with national efforts.

The second option therefore consists of keeping national definitions for forests and adopting one common framework of reporting by major categories. This approach is the one taken in the Intergovernmental Panel on Climate Change process, in which FAO and the United Nations Framework Convention on Climate Change (UNFCCC) (FAO, 2006, 2010; UNFCCC, 2002) define forest as land in which tree cover predominates with a threshold canopy cover of minimum 10–30 percent, height (in situ) of minimum 2–5 m at maturity, and area of minimum 0.05–1.0 ha, where the specific choice of threshold values being defined by each country. Finally, it has been suggested that some national definitions be improved by a stratification according to ecotones, which would apply definitions based on the climate and ecological zone (Philippon *et al.*, 2019).

While it is not possible to harmonize all definitions or classification systems, the language used to build a regional classification can be made interoperable. National forest definitions and land cover classes in the six Central African countries were translated into the International Organization for Standardization (ISO) standard Land Cover Meta Language/Land Cover Classification System (LCML/LCCS) Version 3 to facilitate a regional integration.

A summary of different thresholds used in forest definitions among the Congo Basin countries is presented in Table 2.

Table 2. Forest definitions used on national, regional and global scales

Scale	Minimum area (ha)	Tree height (m)	Canopy cover (%)	Comment	Source
Global	–	–	10%	Distinguish closed forest (canopy cover greater than 40%) and open forest (canopy cover 10–40%).	Gibbs *et al.*, 2010[i]
	0.5	5	10%	–	Bustamante *et al.*, 2016[ii]
	0.5	5	10%	–	Sandker *et al.*, 2017[iii]
	0.5	5	10%	Excludes land that is under agricultural or urban land use.	FAO, 2020[iv]
	0.5–1.0	–	10–30%	An area of more than 0.5–1.0 ha with a minimum tree crown cover of 10–30%.	UNFCCC, 2002[v]
	0.5	5	10%	–	CBD, 2006[vi]
	–	–	–	Proposal of multilingual terminologies and collection of national criteria.	Dobbertin and Prüller, 2002[vii]
	–	–	–	Historical overview of forest concepts and definitions, linking them with distinct perspectives and management objectives.	Chazdon *et al.*, 2016[viii]
	–	–	–	An evaluation of the need for consistent forest definitions.	Lund, 2014[ix]
	0.09	–	50%	Change is defined at pixel scale.	Hansen, 2013[x]
Regional	0.5	5	25%	–	Tyukavina *et al.*, 2018[xi]
Cameroon	0.5	3	10%	Exclusion of monospecific agro-industrial plantations with a purely economic vocation and under agricultural management techniques. May include areas that are the result of natural disturbances which are likely to recover their past status.	REDD+ National Strategy (MINEPDED, 2008)[xii]
Central African Republic	0.5	5	10%	–	FAO 2020 (Forest Resources Assessment)[xiii]

Scale	Minimum area (ha)	Tree height (m)	Canopy cover (%)	Comment	Source
Democratic Republic of the Congo	0.5	3	30%	A canopy cover criterion of around 50% for an area of 0.09 ha was used during the interpretation of the samples.	Forest Reference Emission Level 2018 (MEDD, 2018)[xiv]
		5	60%	Primary, secondary and wetland forests.	Molinario *et al.*, 2020[xv]
Equatorial Guinea	0.5	5	10%	Trees with a height greater than 5 m or capable of reaching this height in situ. Does not include land subject to predominantly agricultural or urban use.	Forest Reference Level (UNFCCC, 2022)[xvi]
Gabon	0.5	5	10%	–	Global Forest Resources Assessment (FAO, 2020)[xvii]
	0.5	5	30%	Functional definition used by national monitoring system (AGEOS).	Sannier *et al.*, 2016[xviii]
Congo	0.5	5	30%	Exclusion of agricultural activities, in particular palm groves in production.	Forest Reference Emission Level (Coordination Nationale REDD, 2017)[ixx]

Note: Defined by minimum area, canopy cover and canopy height.
Sources: See subsection, Table 2, in the References section.

Definitions of deforestation and degradation

FAO provides a generally accepted definition of deforestation as the conversion of forest to other land use (FAO, 2020). This definition includes permanent reduction of the tree canopy cover below the canopy cover threshold used for forest definition. For the purposes of this study, we are explicitly interested in anthropogenic sources of deforestation that arise from land-use and land-cover change, as well as degradation events caused directly by human activity, extraction or interference.

Meanwhile, forest degradation definitions vary widely, and there is an urgent need for standard operational definitions to support monitoring, decision-making and restoration efforts (Sasaki and Putz, 2009). Many definitions for degradation, such as the reduction of ecosystem service delivery, are very broad and difficult to quantify. For the purposes of this research, we define forest degradation – in contrast to deforestation – as a permanent or temporary change in forest cover that does not fall below the established forest definition threshold (Box 1). Operational definitions enable the assessment of deforestation separately from degradation through remote sensing and visual interpretation approaches.

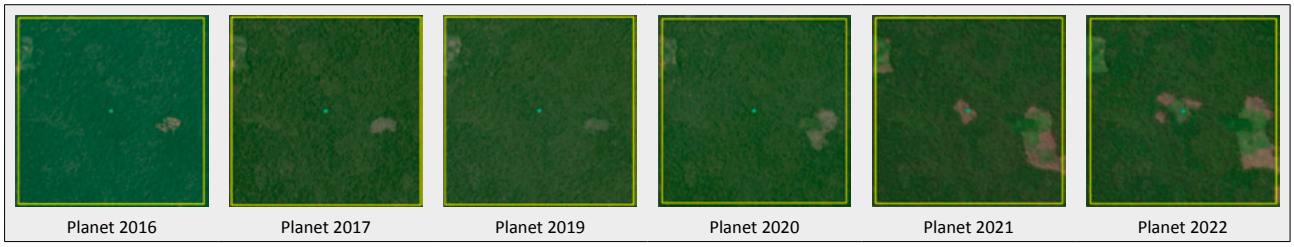
Table 3. Operational project definitions of deforestation and degradation

Deforestation	Degradation
1. refers to permanent reduction of forest cover below the forest definition; 2. includes conversion of forest to other land use, such as agriculture, pasture, mineral exploitation or development; 3. excludes areas of planned deforestation, such as timber extraction, or in areas where the forest is expected to regenerate naturally or with silvicultural methods; and 4. includes areas where impacts, overexploitation or environmental conditions prohibit regeneration above the forest cover definition.	• refers to a temporary or permanent reduction of forest cover that remains above the forest definition; and • includes areas where timber is exploited or trees are removed, as well as where forest may be expected to regenerate naturally or with silvicultural methods.

Example of deforestation

Deforestation is recognizable in images through a permanent change in forest cover. In high-resolution images, we can often see bare ground, felled trees, and sometimes the beginning of agriculture or other driving activities.

Figure 3. Example of deforestation



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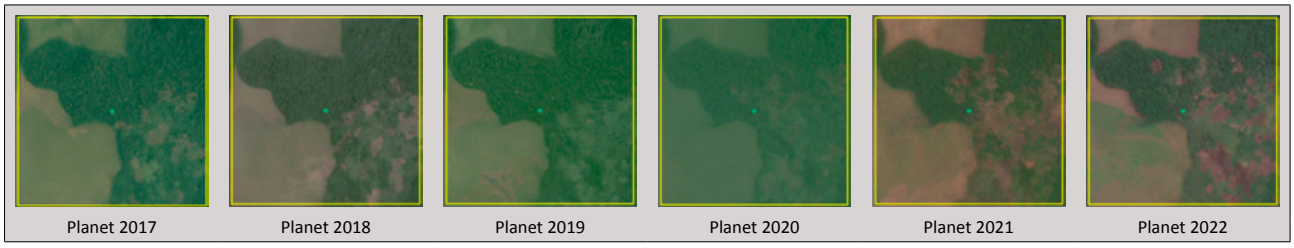
Sources: Authors' own elaboration made in: CEO. 2025. CEO. https://www.collect.earth

Example of degradation

Degradation is more difficult to determine because it involves more subtle changes and can be temporary – sometimes a few trees removed – and the tree cover ultimately remains above the national definition of forest. It is therefore necessary to look at the whole time series and make sure that the changes are not permanent deforestation. Degradation is also not the same everywhere and will differ by forest type and environmental and human context.

Figure 4. Example of degradation



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Sources: Authors' own elaboration made in: CEO. 2025. CEO. https://www.collect.earth

Date convention

The period of interest for this study is 2015–2020, with an assessment of changes from 31 December 2015 to 31 December 2020. The year 2015 was used as the baseline, with the detection of annual changes in deforestation and degradation from 2016 through 2020. This fits with the availability of Sentinel satellite imagery in 2015 (although incomplete for that year), as well as new monthly high-resolution mosaics available for the tropics from Planet, which are available from 2015 to 2020 and used for additional validation.

The following date convention was adopted: a product for the year YYYY is considered as of 31 December YYYY. This convention allows a consistent approach to assessing change products. A change map from Year 1 to Year 2 will be consistent with both Year 1 and Year 2 maps. The status of the year considers any changes that occurred during the year.

Pilot study area: Central Africa

The six countries of Central Africa are home to the largest continuous tract of tropical forest in Africa, a crucial biome supporting global climate, rainfall and water cycles (Washington *et al.*, 2013; de Wasseige *et al.*, 2015). The region is known for its largely intact forests (Grantham *et al.*, 2020; Shapiro *et al.*, 2021b) and globally significant carbon stocks (Dargie *et al.*, 2017; Harris *et al.*, 2021; Pan *et al.*, 2011). These ecosystems provide a critical role effectively regulating regional and global climate, as well as providing important cultural, social and natural resources to more than 60 million people living in or around these ecosystems (de Wasseige *et al.*, 2015). The region hosts unique biodiversity, including over 10 000 species of tropical plants (one-third of which are endemic to the region), over 1 000 species of birds, 450 mammal species, 700 kinds of fish and almost 300 unique reptiles (de Wasseige *et al.*, 2012). The region is known for its unique great apes, including the Bonobo endemic to the Democratic Republic of the Congo, as well as species of lowland and western gorillas, African chimpanzees and forest elephants – which are crucial components of the forest ecosystem, as mammals are important seed dispersers which keep the forest diverse and regenerating. Compared to other continents, the Central African region has a relatively lower annual deforestation rate (Tchatchou *et al.*, 2015), which suggests that African forests are overall more intact. However, a recent assessment of forest integrity shows that the Amazon has a larger proportion of healthy forests than Africa (Grantham *et al.*, 2020), which is more likely due to the more gradual and subtle impacts of forest degradation, versus concentrated, large-scale deforestation in South America. More critically, the degradation rate in Central Africa has been shown to be sharply increasing in recent years which is a cause for concern (de Wasseige *et al.*, 2015; Tchatchou *et al.*, 2015).

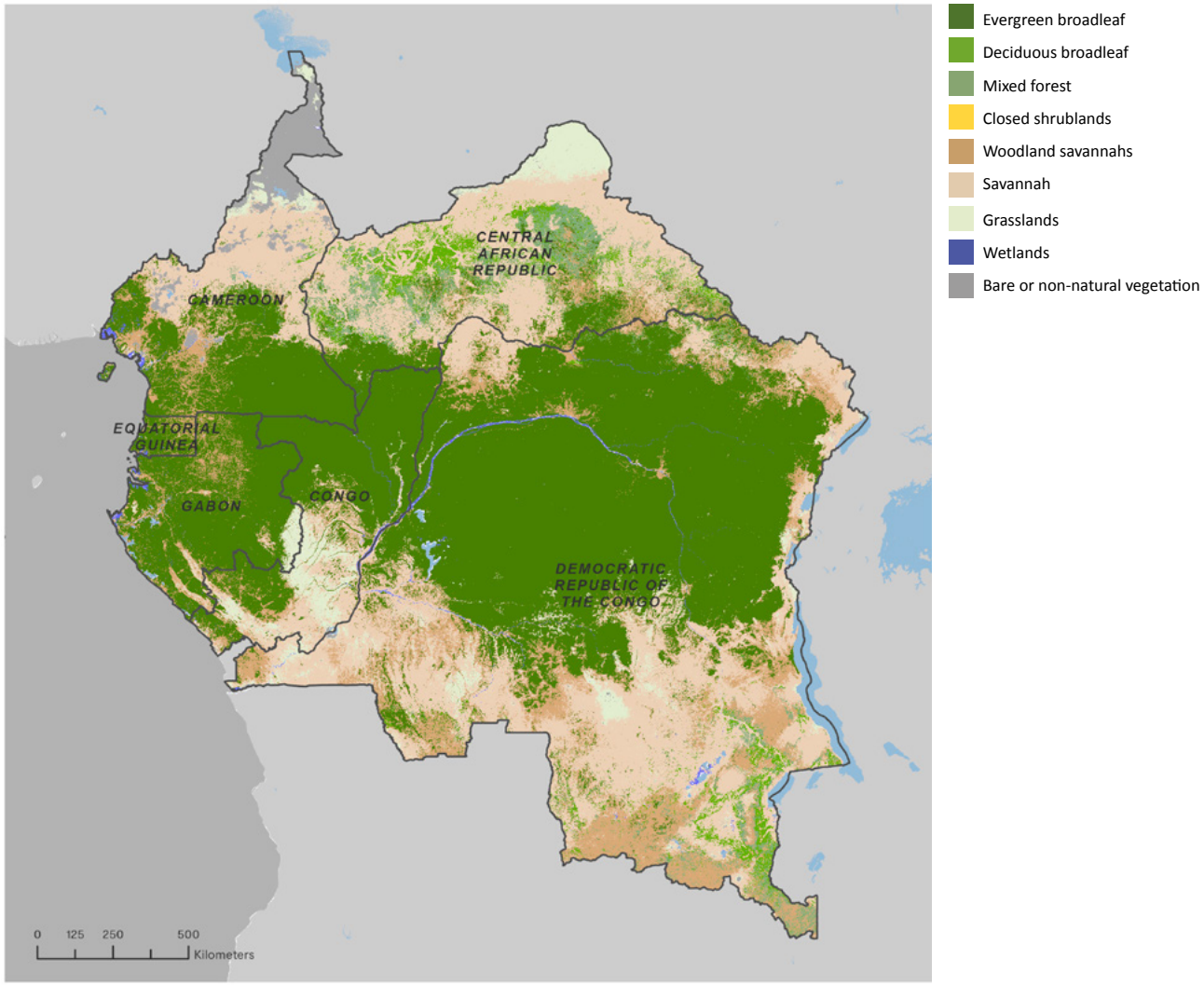
Low access to infrastructure – notably electricity – (IEA, 2022), high reliance on natural resources, and rapid population growth, coupled with vulnerability to climate change, are expected to place additional pressures on these forests. The region scores relatively low on the human development index (United Nations, 2013), signalling the potential for rapid economic growth that can significantly increase existing pressures on natural ecosystems (Megevand *et al.*, 2013; Tchatchou *et al.*, 2015) – creating a complex situation to meet the needs for sustainable development investments and global climate targets, all while ensuring food security (Mosnier *et al.*, 2014).

International efforts to conserve and secure Central African forests have been addressed via various initiatives to address the tropical forest belt. Through a collaborative partnership between international donors supporting strategic, country-level REDD+ and low emission development investments in the six Central African high-forest cover countries, CAFI has the objective to recognize and preserve the value of the forests in the region to mitigate climate change, reduce poverty and contribute to sustainable development. The Commission des Forêts d'Afrique Centrale (COMIFAC)[5] (The Central African Forest Commission) was born out of the Yaoundé declaration, which unites forest conservation activities in ten Central African countries (Burundi, Chad, Rwanda, and Sao Tome and Principe, in addition to the six countries presented in this publication). This regional body is tasked with addressing political harmonization between countries to foster sustainable forest use, financing the development of the forestry sector, reduction of illegal wildlife trade and poaching. The United States Agency for International Development (USAID) has implemented the Central African Regional Program for the Environment (CARPE),[6] which supports similar efforts related to the conservation of forests, biodiversity and capacity building. All of these regional approaches provide considerable support to transboundary efforts and themes common to all countries, fostering South–South exchange and collaboration.

[5] https://comifac.org

[6] https://carpe.umd.edu

Figure 5. The study area covering six countries of Central Africa



Notes: The study area covers six countries of Central Africa (Cameroon, the Central African Republic, the Congo, the Democratic Republic of the Congo, Equatorial Guinea and Gabon), including more than 4.04 million km^2 of various forest types and savannahs. Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Data from: GEE. 2025. GEE. https://earthengine.google.com. Map created in: ESRI. 2012. ArcGIS Pro. Version 3.5.2.

The study area includes the national boundaries of the six Congo Basin countries: Cameroon, the Central African Republic, the Congo, the Democratic Republic of the Congo, Equatorial Guinea and Gabon.

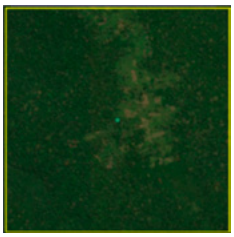
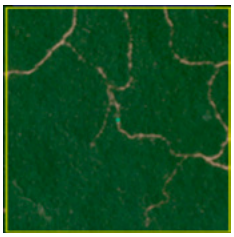
Because of consistency issues between border datasets at national, regional and global levels, it was decided by the partners to select and use one global dataset, the Large Scale International Boundaries (LSIB), to define international borders.[7]

Driver definitions

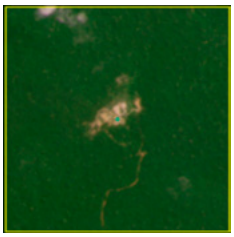
A total of eight direct drivers were selected using guidance from Geist and Lambin (2002) and defined according to specific characteristics identifiable in high-resolution satellite imagery from Planet. The drivers and their criteria are described in Table 3. Any observation not falling into these categories (for example natural change) was labelled “other”.

[7] https://catalog.data.gov/dataset/large-scale-international-boundaries

Table 4. Driver definitions and characteristics

Driver	Characteristics
Artisanal agriculture © FAO/Collect Earth 	Small-scale agriculture is composed of small, informal, unstructured and irregular agricultural plots covering an area of less than 5 ha. The presence of fires (slash-and-burn agriculture) can be observed, and the land is often covered in various stages of cultivation.
Industrial agriculture © FAO/Collect Earth 	Industrial agriculture is characterized by agricultural areas larger than 5 ha that tend to be homogeneous and often consist of a single crop. In some cases, agriculture may be more varied and consist of many large fields closely packed together. Therefore, large areas consisting of many small fields cultivated at the same time are also considered industrial agriculture under the definition.
Infrastructure © FAO/Collect Earth 	Roads are visible in the images with linear features and are identified as motorized when they are wide enough (5 m) to carry vehicle traffic. Small irregular walking paths through vegetation are not included. Roads can be large highways or logging trails, and are most often found with other engines such as villages and mining facilities.
Settlements © FAO/Collect Earth 	Villages and settlements can be hard or soft-roofed, buildings or huts, and they are often accompanied by roads and other drivers such as small-scale agriculture. This driver can be an urban area or a small, isolated village.
Artisanal forestry © FAO/Collect Earth 	Small-scale or artisanal logging is characterized by the selective extraction of trees in an irregular manner, leaving a tree cover. These are areas that are not visibly cultivated; they are often found in places accessible by small roads or villages.
Industrial forestry © FAO/Collect Earth 	Large-scale or industrial forestry is recognizable by the presence of logging roads, along which selective logging degradation occurs. These roads may be recent or old, and the canopy can quickly cover them after they are created; therefore, all years of imagery acquired over the entire study period are evaluated.

Artisanal mine



© FAO/Collect Earth

Small-scale mining is characterized by muddy clearings and usually ponds or water catchments; may feature turbid water. Artisanal in nature, the clearings are generally small, isolated and located along streams.

Industrial mine

© FAO/Collect Earth

Large-scale mining is characterized by large ponds, open pits and clearings, and extensive infrastructure and roads.

Sources: Authors' own elaboration made in Collect Earth Online basemap (https://www.collect.earth)

Approaches for monitoring forest disturbance

There is a growing need to monitor, understand and promptly react to forest disturbances – especially degradation – before restoration is too costly or the impacts are too extensive to reverse. Whether part of a framework to reduce forest-related carbon emissions or a prioritization for conservation interventions, there is an increasing reliance on accurate, reliable scientific data derived from satellite earth observation to improve our knowledge of these dynamics for natural forest systems. Remote sensing provides a consistent, holistic and efficient method to monitor forests over time. Satellite earth observation is possible through a number of freely available or commercial sensors, which rely on optical or cloud-penetrating active radar, so that practically any forest in the world can be imaged at least once a week.

Countries are actively getting involved in international initiatives to mitigate climate change, notably those facilitating the financing of results-based payments. The associated carbon accounting needs to be as transparent, robust and cost-effective as possible. Given the need to monitor and quantify deforestation and forest degradation over long time periods consistently, repeatedly and at large scales, remote sensing and earth observation are providing the most efficient solutions (GOFC-GOLD, 2014). Satellite imagery is an effective tool to monitor forest ecosystems at many scales; advantages include consistency, transparency, accuracy and timeliness (Herold *et al.*, 2011).

Remote sensing plays a critical role in climate change projects through monitoring, reporting and verification (MRV), and the establishment of reference levels, which are the baselines through which deforestation reduction success is evaluated (Hosonuma *et al.*, 2012; Mitchell, Rosenqvist and Mora, 2017). The bold commitments by the international community and results-based finance to encourage countries to reduce and slow deforestation need to be supported by accessible, credible technology to inform forest policies (Neeff and Piazza, 2020). The selection of appropriate data to meet these challenges is very important (Sandker *et al.*, 2021), as are repeatable, understandable and transferrable technologies that will function for time periods sufficient in length.

Since the early 1990s, changes in forest area have been monitored from space with acceptable accuracy (Achard *et al.*, 2002, 2004). Some countries, such as Brazil and Indonesia, have a had a well-established operational systems in place for over a decade; others are still developing these capabilities (DeFries *et al.*, 2007). Consistent, reliable remote sensing approaches are essential to detect forest change using methods that can be categorized into either: indirect approaches, which estimate proxies or indicators; and direct approaches, which measure remotely sensed variables or indicators (DeVries *et al.*, 2015; Herold *et al.*, 2011).

There have been many targeted efforts in the last decade to accurately estimate deforestation and forest degradation over time using earth observation data, as well as help countries meet their climate targets and engagements. These datasets provide unprecedented, up-to-date information on various aspects of forest change for global or tropical forests. While there is a great scientific interest in providing wall-to-wall global forest data products and analysis, these data alone are often not sufficient for robust, accurate deforestation estimates and trends (Sandker *et al.*, 2021), and are often not relevant to decision-making at national or subnational scales. Countries are more likely to use, understand and value data they produce and update themselves, and can apply to national forest monitoring systems for decision-making and implementation of policies. Given the release of freely available satellite data and the need for comprehensive forest monitoring, there has been an associated increase in interoperable open-source, cloud-based platforms to provide toolkits for remote sensing, land cover mapping and forest monitoring (Tenneson *et al.*, 2018), including Google Earth Engine (GEE)[8] and SEPAL.[9]

Global forest change datasets generated from satellite data, such as Landsat data, can provide annual information on forest loss and gain for anywhere in the world (Hansen *et al.*, 2013). However, the use and direct application of these datasets should consider potential errors or caveats. For example, the global forest change product provided by the University of Maryland does not specifically identify deforestation; rather, it identifies tree cover loss, which may be different, particularly in relation to operational definitions of forest and deforestation. Furthermore, it does not differentiate between tree crops and natural forests and needs to be contextualized to provide relevant information. In many African forest landscapes, forest disturbance occurs on a small spatial scale (DeVries *et al.*, 2015; Fisher, 2010; Tyukavina *et al.*, 2018), making the underestimation of forest loss by global or regional forest change datasets in these landscapes highly likely (Milodowski, Mitchard and Williams, 2017; Tropek *et al.*, 2014).

For some countries with low monitoring capacity, simpler proxies can be used to assess changes in forests over time, such as the matrix approach recommended by Bucki *et al.* (2012). In order to reward activities in the context of result-based payments for emissions reduction, an approach to conservativeness is realistic and recommended (Grassi *et al.*, 2013). General categories or forest types can be evaluated and tracked over time through an intactness matrix, shown in Table 4 (Bucki *et al.*, 2012). This has the advantage of being clear, understandable, repeatable, and particularly relevant when expensive carbon monitoring systems are not in place or available. These represent meaningful performance indicators that can be measured and rewarded in the context of a REDD+ program.

Table 5. REDD+ activity matrix describing forest transitions

	To		
From	Natural/intact	Non-intact	Other land
Natural/intact	Forest conservation	Forest degradation	Deforestation
Non-intact	Afforestation or reforestation	Sustainable management	Deforestation
Other land	Conversion to non-intact	Afforestation or reforestation	Stable non-forest

Source: Bucki, M., Cuypers, D., Mayaux, P., Achard, F., Estreguil, C. & Grassi, G. 2012. Assessing REDD+ performance of countries with low monitoring capacities: the matrix approach. Environmental Research Letters, 7(1): 014031–014043. https://doi.org/10.1088/1748-9326/7/1/014031

[8] https://earthengine.google.com

[9] https://sepal.io

Monitoring intiatives can also include the observation of the presence of logging roads which might incur deforestation (Brandão and Souza, 2006). Other approaches use spatial pattern, such as fragmentation from MSPA or buffering, to assess forest degradation of changes in forest status over time (Broadbent *et al.*, 2008; Chaplin-Kramer *et al.*, 2015; Haddad *et al.*, 2015; Potapov *et al.*, 2017; Riitters *et al.*, 2015; Shapiro *et al.*, 2016; Tyukavina *et al.*, 2016).

Still, indirect methods remain relatively simple. More robust approaches should be integrated into monitoring systems, including direct carbon monitoring and associated uncertainty estimates, in order to keep confidence and robustness of an international marketing scheme high (Yanai *et al.*, 2020). As the impacts of degradation can vary widely, it would be beneficial to include, at the very least, categories of degradation, continuous estimations related to intactness (Grantham *et al.*, 2020; Venter *et al.*, 2016), or timing of disturbances (Vancutsem *et al.*, 2021), which can provide finer granularity and follow more in accordance with the temporal definition of degradation.

With recent improvements in data availability and processing capacity, direct remote sensing approaches (Souza, 2003; Souza and Roberts, 2005) can integrate large volumes of data for dense time-series analysis or indicator assessments (Goetz *et al.*, 2015; Mitchell, Rosenqvist and Mora, 2017; Tewkesbury *et al.*, 2015). New developments using synthetic aperture radar (SAR) have provided promising results for direct detection in the cloudy tropics (Reiche *et al.*, 2021). However, capacity development is necessary for implementation and is not consistent between countries (Romijn *et al.*, 2015), and approaches that have been developed in other continents may not always be transferable to the Central African context.

Linkages between degradation and deforestation

Degradation has been shown to be a precursor for deforestation: between 17 and 57 percent of already degraded forest has been estimated to be eventually deforested in Central Africa (Gaston *et al.*, 1998; Shapiro *et al.*, 2016; Vancutsem *et al.*, 2021). Therefore, the detection of degradation could serve as a warning system to prevent more permanent impacts.

Methods

The solutions to assess deforestation, forest degradation and associated drivers uses FAO's Open Foris Solutions, including SEPAL for satellite data analysis, as well as Collect Earth Online (CEO) and Google Earth Engine (GEE). The approach analyses dense satellite time series to generate geospatial data on forest changes, which are then validated and interpreted for direct drivers in four major steps:

- **Step 1:** Process optical (Landsat 4, 5, 7 and 8) and radar (ALOS PALSAR)[10] satellite images to create wall-to-wall maps of vegetation types through supervised classification, recoded to a binary forest mask (following national forest definitions) and a forest fragmentation assessment for the baseline year 2015.
- **Step 2:** Process optical satellite (Landsat 4, 5, 7 and 8) time series data covering 2012–2020 (using 2012–2015 as the historical time period and 2016–2020 as the monitoring period), using dense time-series detection algorithms to produce a forest change map for 2015–2020 at the regional scale, identifying areas of both deforestation and degradation.
- **Step 3:** Conduct stratified random sampling on the change map from Step 2, perform systematic validation for all change points, plus a sample of stable points in Collect Earth Online, evaluating land cover types, changes and dates of change, and the identification of the presence of direct drivers.
- **Step 4:** Quantify direct drivers by forest types and fragmentation class.

Figure 6. Overview of the Open Foris Solutions

Ground
Simple, intuitive and versatile map-first data collection mobile application
Arena Mobile
The fast, new generation data-collection tool Arena Mobile works with Arena and runs on Android and iOS devices
Collect Earth
Augmented visual interpretation tool for land monitoring
Collect Earth Online
Custom built, open-source, high-resolution satellite image viewing and interpretation system
Collect
Easy and flexible survey design and data management
Arena
Online platform for survey design, data management, utilization and processing
SEPAL
System for Earth observation data access, processing, analysis for land monitoring
Earth Map
The power of Google Earth Engine without coding. A user-friendly tool for complex land monitoring

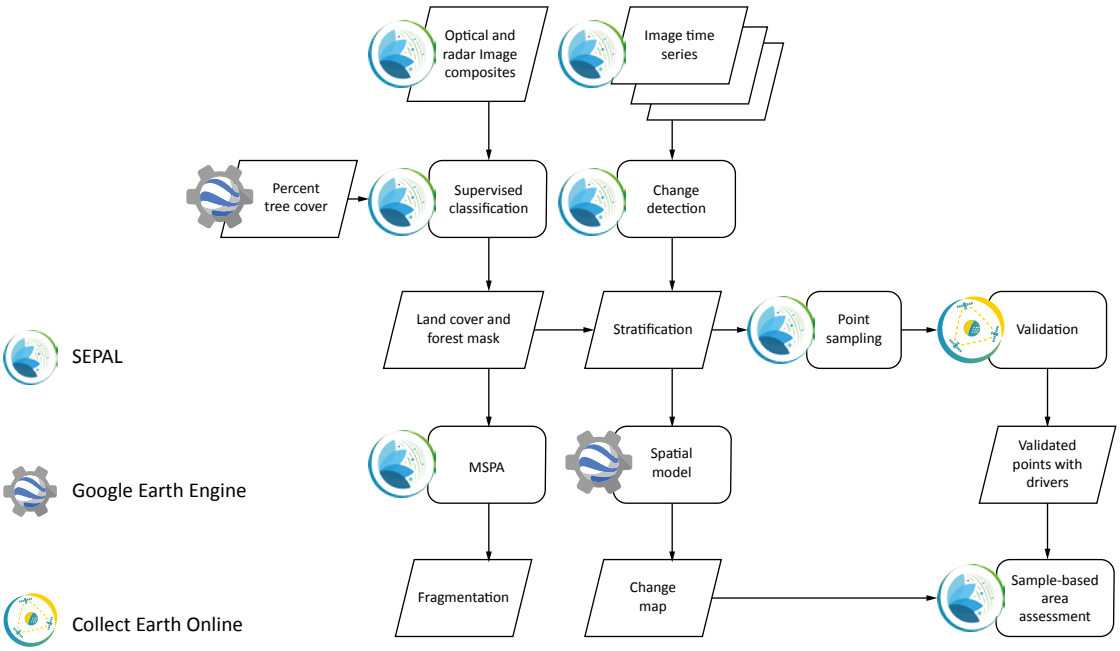
Note: https://openforis.org

[10] ALOS PALSAR refers to the Advanced Land Observing Satellite Phased Array type L-band Synthetic Aperture Radar.

To assess annual forest trends, a dense time-series analysis is conducted, which processes all available image sources over the desired time period. This enables the detection of changes or breaks, which can be attributed to deforestation or degradation. Several approaches were defined, reviewed and evaluated (Table 5) in the context of the objectives of the project, in order to accurately discern deforestation from degradation and no change in the 2015–2020 time period, as well as identify and quantify the associated direct drivers.

The overview of the methodology with the appropriate software used is shown in Figure 4.

Figure 7. Methodological approach

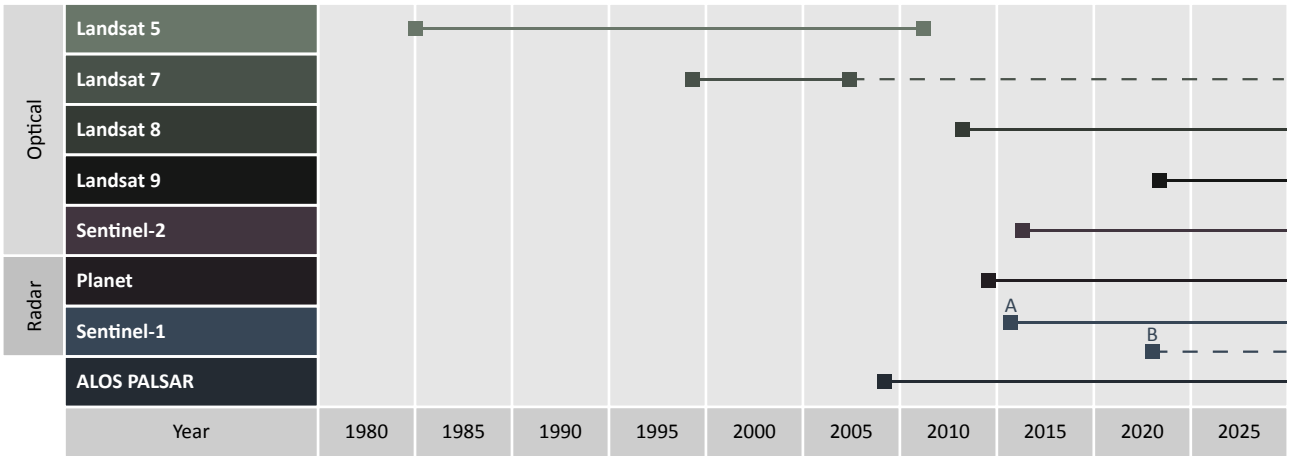


Note: This approach is executed in SEPAL and Google Earth Engine, with validation performed in Collect Earth Online. MSPA refers to morphological spatial pattern analysis.

Data sources

Satellite remote sensing remains the principal source of consistent, reliable, wall-to-wall information for monitoring forests. Several data sources are available for time-series analysis, but each satellite sensor has advantages and disadvantages in terms of long-term consistent coverage, resolution, file size and data gaps. The requirements for time-series analysis are repeated data collections over time, including prior to the study period with consistent spectral properties, and sufficient resolution to detect forest canopy disturbance. For these reasons, Landsat is often chosen as the primary data source for the change analysis due to its consistent data acquisition over the project time period, repeat visit time, multiple spectral bands and resolution.

Figure 8. Overview of the available archive satellite data



Note: The dotted-line represents the time after the Landsat 7 scanline error; the satellite mission ended in April 2022. Landsat 5 was decommissioned shortly after the launch of Landsat. The Sentinel-1 mission is comprised of 2 sensors – Sensor B failed in December 2021.

Through Norway's International Climate and Forests Initiative (NICFI),[11] users can access Planet's high-resolution, analysis-ready mosaics of the world's tropics to help reduce and reverse the loss of tropical forests, combat climate change, conserve biodiversity and facilitate sustainable development for non-commercial uses. This dataset provides essential temporal information to validate deforestation and degradation events, and identify direct drivers, on the period covered by this study.

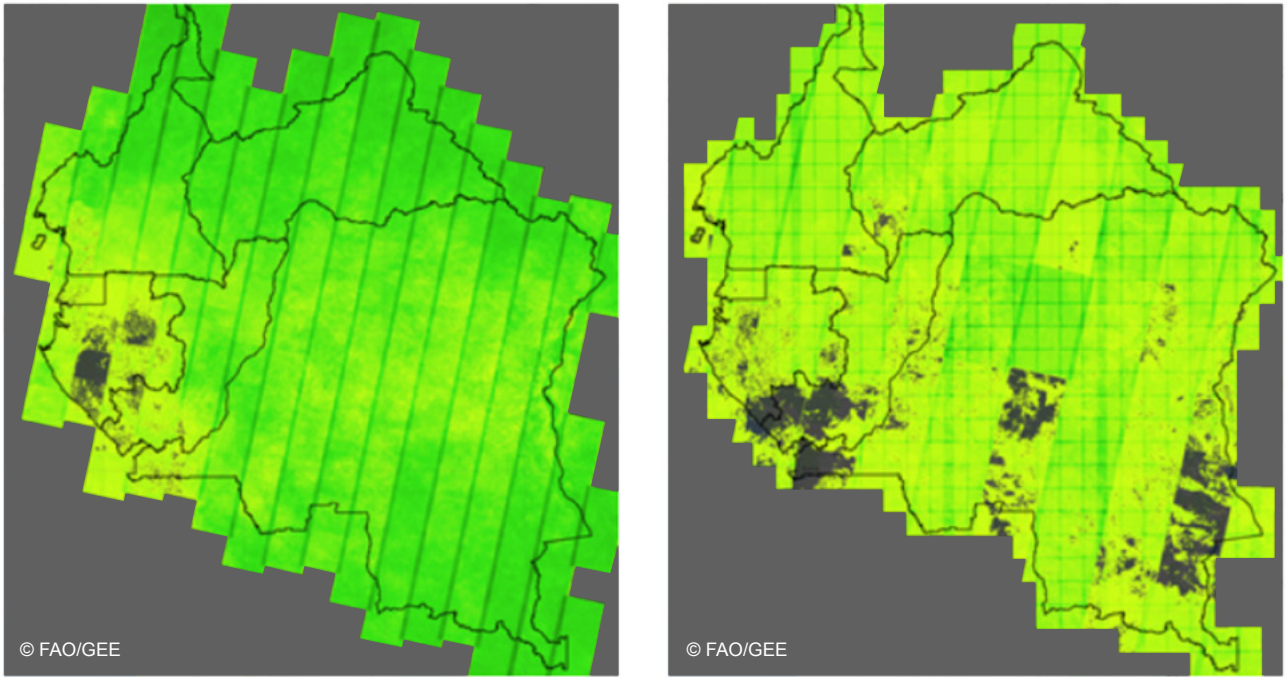
Table 6. Review of available satellite data sources for monitoring deforestation and degradation

Sensor	Advantages	Disadvantages
Landsat	Consistent acquisition since 1983 with several sensors building a historical time series; shortwave infrared (SWIR) and near infrared (NIR) spectral bands useful for vegetation monitoring.	Data gaps in 2013–2015 due to Landsat 7 scanline error.
ALOS PALSAR	Cloud-free, ready-to-use data for 2015–2018.	Data are pre-processed (not raw) and provided annually with topographic artefacts.
Sentinel-1	Higher resolution (10–20 m), active radar is independent of cloud cover, full coverage in 2021.	Topographic artefacts, incomplete coverage in 2015.
Sentinel-2	Higher resolution (10–20 m) and SWIR, NIR and red-edge spectral bands are useful for vegetation monitoring.	High data volumes, incomplete coverage in 2015.
Planet mosaics (from NICFI)	High-resolution (5 m), biannual and monthly repeat coverage.	Data gaps in 2015, limited spectral resolution, inconsistent geopositioning and data values between satellites, large data volumes.

[11] https://www.planet.com/nicfi

Due to clouds and data acquisition strategies, there are varying levels of coverage for all sensors used. It is recommended to combine these as best as possible to maximize coverage, while relying on Landsat for baseline years, which provides the most consistent cloud-free coverage up to the end of 2015. When possible, Sentinel-2 was also used to complement baseline products (Figure 6). For active radar, ALOS PALSAR provided the most comprehensive coverage (Figure 7).

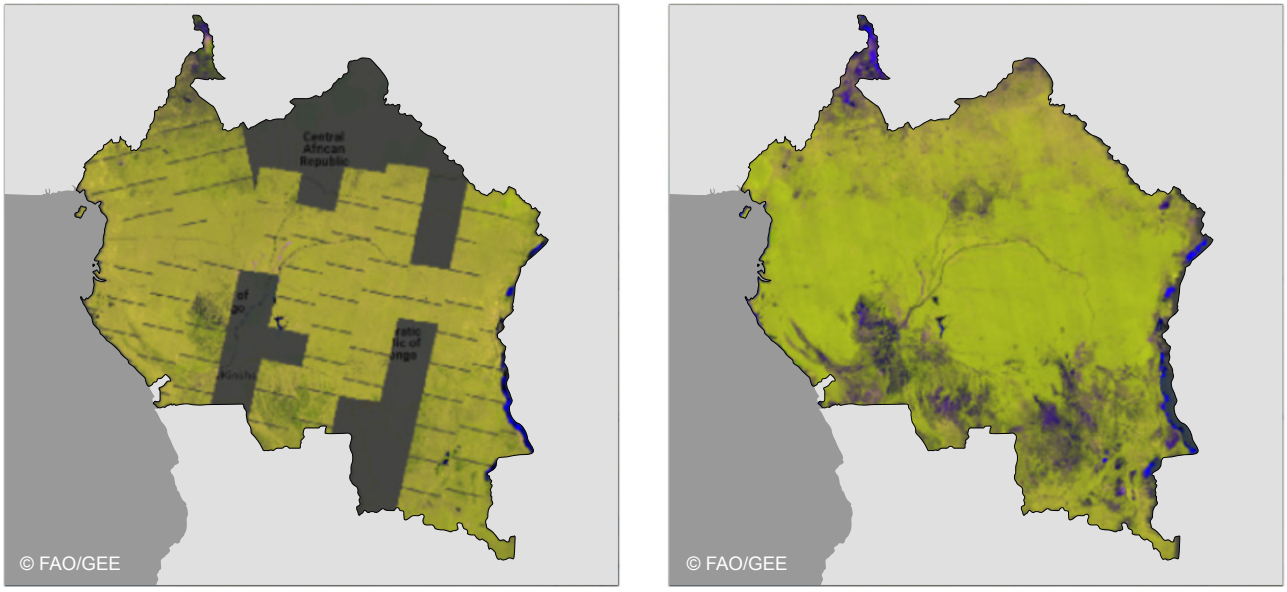
Figure 9. Cloud-free data coverage for Landsat 8 (left) and Sentinel-2 (right), 2015



Notes: Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Authors' own elaboration overlaid upon the Google Satellite basemap in GEE. Map created in: GEE. 2025. GEE. https://earthengine.google.com

Figure 10. Available data coverage of Sentinel-1 (left) and ALOS PALSAR (right), 2015



Notes: Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Authors' own elaboration overlaid upon the Google Satellite basemap in GEE. Map created in: GEE. 2025. GEE. https://earthengine.google.com

Baseline mapping

Wall-to-wall products are required for the baseline year of the study (for Central Africa: 2015) and include a percent tree cover product, land cover, a forest mask and a fragmentation map.

Tree cover percentage

A regional percent tree cover map for the baseline year can be created by upscaling forest/non-forest maps generated from Planet image samples (5 m) in order to apply national forest definitions. In Central Africa, a percent forest cover value was estimated at the 30 m pixel scale for 12 sample Planet images in the region, with forest and non-forest identified by visual interpretation to train a random forest model. The percent cover estimates from sample scenes were then used to train a coarser random forest regression model applied to ALOS and Landsat composites, including 19 derived spectral indices, producing a continuous tree cover estimate from 0 to 100 percent.

Regional land cover

When working on a regional scale, different national forest definitions can complicate consistent assessment. This section outlines the development of a baseline land cover map for Central Africa derived from a common classification system (Dalimier et al., 2022), validated by the the project technical committee and included all land cover classes referenced in national systems (Table 7). This land cover classification has been published in the FAO Land Cover Registry.[12]

Table 7. Regional classification system

Raster code	Forest/ non-forest	English	French	Spanish	Description
1	Forest	Dense forest	Forêt dense	Bosque denso	Dense humid primary evergreen forest on terra firme, greater than 60% tree cover
2	Forest	Dense dry forest	Forêt dense sèche	Bosque denso seco	Dense dry forest, greater than 60% tree cover with dry seasons
3	Forest	Secondary forest	Forêt secondaire	Bosque secundario	Open forest, 30–60% tree cover, degraded or secondary
4	Forest	Dry open forest	Forêt claire sèche	Bosque claro seco	Dry open forest, 30–60% tree cover with dry seasons
5	Forest	Sub-montane forest	Forêt sub-montagnarde	Bosque sub-montañoso	Forest with greater than 30% tree cover, 1 100–1 750 m altitude
6	Forest	Montane forest	Forêt montagnarde	Bosque montañoso	Forest with greater than 30% tree cover, greater than 1 750 m altitude
7	Forest	Mangrove	Mangrove	Manglar	Forest greater than 30% tree cover on saline waterlogged soils
8	Forest	Swamp forest	Forêt marécageuse	Bosque pantanoso	Swamp mixed forest, greater than 30% tree cover, flooded more than 9 months
9	Forest	Gallery forest	Forêt galerie	Bosque en galería	Riparian forest in valleys or along river edges
10	Forest	Mature forest plantation	Plantation forestière mature	Plantación forestal madura	Tree cover greater than 15%, cultivated or managed
11	Forest	Woodland savannah	Savane arborée	Sabana arbórea	Woodland savannah 15–30%, tree cover or greater than national forest definition
12	Forest*	Shrubland savannah	Savane arbustive	Sabana arbustiva	Shrubland savannah greater than 15%, shrub cover or greater than national forest definition

[12] https://www.fao.org/hih-geospatial-platform/resources/projects/land-cover-legend-registry/en

Raster code	Forest/ non-forest	English	French	Spanish	Description
13	Non-forest	Herbaceous savannah	Savane herbacée	Sabana herbácea	Grassland savannah greater than 15% tree cover
14	Non-forest	Aquatic grassland	Prairie aquatique	Pradera acuática	Regularly flooded grassland
15	Non-forest	Bare land	Sols nus-végétation éparse	Suelo desnudo-vegetación escasa	Greater than 15% vegetation cover
16	Non-forest	Cultivated areas	Terres cultivées	Tierras cultivadas	Cultivated vegetation, greater than 15% vegetation cover
17	Non-forest	Developed areas	Zones bâties	Zonas edifiadas	Human dominated and artificial surfaces
18	Non-forest	Water	Eau	Agua	Water greater than 50%
19	Non-forest	Shrubland savannah	Savane arbustive	Sabana arbustiva	Shrubland savannah greater than 15% tree cover less than national forest definition

Note: *In Cameroon and the Central African Republic, shrub savannahs were identified as forest, in adherence to the national forest definitions of greater than 10 percent tree cover.

A regional map of land cover was produced using the SEPAL classification module with training data from 1 004 samples compiled in Collect Earth Online, which provides various image sources in a web browser and an interactive form to identify the land cover class present. Additional training data included 225 sample points for swamp forests and 83 points for terra firme forests provided by the FAO peatlands project, as well as 862 samples of dense dry forest from national partners in Democratic Republic of the Congo and 16 samples from Equatorial Guinea.

The image classification module in SEPAL can use several data sources, which can include the following:

- optical image mosaic for the baseline year;
- ALOS PALSAR radar mosaic;
- percent tree cover;
- National Aeronautics and Space Administration (NASA) elevation data; and
- a topographic index.

A random forest algorithm with 30 trees was applied to the input images. Since the ALOS PALSAR mosaic has no data values for topographic shadows, and may introduce no data areas in the final map, two classifications were performed, one with and one without the ALOS mosaic. These were then combined in the post-classification cleaning step performed in Google Earth Engine. This included the following:

- **Step 1:** Import and reclass the SEPAL code output to the CAFI classes for drivers of deforestation and degradation, as described in Table 6.
- **Step 2:** Remove holes in the ALOS data by integrating two classifications: one run with the ALOS PALSAR composite and one without.
- **Step 3:** Integrate data from the Global Human Settlement (GHS) dataset (Pesaresi *et al.*, 2016) to correct and add built-up areas.
- **Step 4:** Assign open and closed forests according to the tree cover percent.
- **Step 5:** Define montane and sub-montane forest according to elevation criteria from NASADEM[13] (NASA JPL, 2020).
- **Step 6:** Use digital elevation and European Space Agency (ESA) Worldcover layer (Santoro *et al.*, 2021) to remove any erroneous inland mangroves and reclass them to swamp forest.

[13] NASADEM refers to NASA's Digital Elevation Model.

- **Step 7:** Use areas of non-permanent water defined by the JRC Global Surface Water Product (Pekel *et al.*, 2016) to correct and identify additional aquatic grasslands.
- **Step 8:** When official data exist in map form they are integrated into the regional map. National land cover data for 2015 provided by Gabon replace the regional classification. We also include available land cover data for Annobón, Equatorial Guinea which does not have sufficient satellite imagery coverage.
- **Step 9:** The classification is recoded to forest/non-forest according to national forest definitions using percent tree cover, height. In the Central African Republic, areas of sparser savannah (shrub savannah) are recoded to forest to adhere to the national forest definition (greater than 10 percent tree cover).

Fragmentation

Forest fragmentation, which discerns intact continuous forest areas from edges and patches, was estimated for 2015 using MSPA from Guidos Toolbox (more specifically the more powerful Guidos Workbench)[14] using an edge width of 9 pixels (270 m). The outputs from MSPA Fragmentation are recoded into five classes: background (0); patches or islets (1); outer edges (2); corridors, loops and bridges (3); inner edges and perforations (4); and core forest (5).

The final fragmentation classes are defined in Table 8.

Table 8. Forest fragmentation classes

Class	Description	Fragmentation
Core	Interior forest area; pixels surrounded by other forest	Low
Inner edge	Forest bordering non-forest perforation inside core forest	
Outer edge	Forest bordering exterior non-forest	
Corridor	Forest pixels connecting core areas	
Patch	Forest islands too small to contain core forest	High

Note: Ordered from intact to most fragmented.

A large intact forest block extends throughout the tropical forest zone in southeast Cameroon, the Congo, the Democratic Republic of the Congo, and Gabon with several large patches in central Cameroon and the Central African Republic.

Forest change detection

There are an abundant number of methods for determining changes in satellite imagery and selection of an appropriate approach depends on the region, availability of imagery, training data, topography and other factors.

Many approaches based on remote sensing have been developed from the various satellite data streams in recent years (Table 9).

[14] https://forest.jrc.ec.europa.eu/en/activities/lpa/gwb

Table 9. An overview of change detection approaches

Change detection approach	Description	Remarks	References
Breaks For Additive Seasonal and Trend (BFAST)	Integrates the decomposition of time series into trend, seasonal and remainder components with methods for detecting change.	Can discern abrupt changes (deforestation) from modelled seasonal dynamics in a variety of forest types, including dry forests and savannahs. Less extreme changes (with smaller magnitude) can be used to detect degradation.	DeVries *et al.*, 2015;[i] Schultz *et al.*, 2018;[ii] Verbesselt *et al.*, 2010.[iii]
Spatial cumulative sum analysis (CUSUM)	Estimates the difference in a variable from its mean measurement over a given time frame.	Initially developed for climate and other data types but can be applied to active radar data or an optical index. Optical data has not been evaluated for detecting degradation.	Kucera, Barbosa and Strobl, 2007;[iv] Manogaran and Lopez, 2018;[v] Ruiz-Ramos *et al.*,vi 2020; Ygorra *et al.*, 2021.[vii]
Forest canopy disturbance monitoring (FCDM)	Detects crown cover disturbance via the difference of the self-referenced normalized burn ratio, which has been processed to remove illumination and topography effects. The delta is the difference between the composites of two reference periods.	Sensitive to canopy changes and degradation. Functionality with optical data is limited to the tropical domain.	Langner *et al.*, 2018.[viii]
Continuous degradation detection (CODED)	A continuously updated difference between multiple observations and a fitted model, capped by thresholds. Results are classified into change.	Is designed for detecting degradation but has also been used for deforestation assessments.	Bullock, Woodcock and Olofsson, 2020;[ix] Bullock *et al.*, 2020.[x]
LandTrendr	Spectral-temporal segmentation algorithms for annual change detection and generating trajectory-based spectral time-series data largely absent of interannual signal noise.	Can detect different trajectories of change (fastest, slowest, longest duration).	Kennedy *et al.*, 2010.[xi]
Continuous change detection and classification (CCDC)	Creates a classification model based on a harmonic time series and applies that classification to new images to detect differences.	Can also be used to produce synthetic cloud-free images.	Zhu and Woodcock, 2012.[xii]

Sources: See subsection, Table 9, in the References section.

The Breaks for Additive Seasonal and Trend (BFAST) change detection algorithm is designed to detect and characterize changes while decomposing seasonal dynamics. This makes it appropriate for the varied forest types in Central Africa, including dry and open forests. It is an iterative process which estimates the timing, magnitude and direction of change (Verbesselt *et al.*, 2010). The GPU BFAST Module[15] in SEPAL is used where the raw outputs consist of a two-band image for each tile, which include the magnitude of change (positive or negative) at the estimated break and the date of the detected break.

[15] GPU refers to graphics processing unit.

The BFAST outputs were post-processed to quantify stable areas from two types of change (deforestation and degradation) for the five years of the study period. Only the negative magnitudes are used in order to determine loss in the Normalized Difference Fraction Index (NDFI), and the magnitude values are used to threshold the changes by forest type. Mean and standard deviation of magnitudes were estimated for each forest type to determine threshold and discern deforestation from degradation. These were then adjusted iteratively as needed to coincide with visible change in Planet mosaics and Tropical Moist Forest deforestation and degradation products. The final BFAST change map for Central Africa contains a total of 139 classes, combining stable land cover (values 1–19), as well as annual degradation for each forest type (values 100–154) and annual deforestation for each forest type (values 200–254).

Furthermore, a cumulative sum analysis – originally developed for big data analysis in the financial sector (Manogaran and Lopez, 2018) and later adapted to active radar data (Ruiz-Ramos *et al.*, 2020) – was designed to assess spatiotemporal trends in the Landsat time series. This algorithm does not require a long historical time period and can accurately detect deforestation with optical imagery (Bullock, Woodcock and Holden, 2020), but is not designed for identifying degradation. The combination of these approaches was used to develop a stratification map from which to extract samples based on area represented in the map.

Area-based sampling strategy

The interpretations of land-use patterns require regional and local knowledge on the ongoing forest change processes. They need to be underpinned by ground observations from either national inventories or data acquired by local experts or participating communities (Danielsen *et al.*, 2011; Pratihast and Herold, 2011). In order to provide a robust calibration, validation and accurate area estimations, all strata of the change map were sampled according to class area, while keeping a minimum number of points per land cover type, type of change and date of change. The number of stable points of dense forest are significantly larger than other classes, which is represented in the sampling strategy. This approach ensures a wide distribution of points – including as many possible points of change in order to assess associated direct drivers in space and time.

Validation of change and drivers using Collect Earth Online

A survey form was created in Collect Earth Online,[16] enabling various users from anywhere to simultaneously assess the entire validation dataset using visual interpretation of the high-resolution imagery (MapBox, Bing, Planet mosaics) available in the interface. Validation was performed at two scales: on the sample point itself and within a 2 km plot around the point. Information on land cover type, change, type of change and date of change were assessed at a 0.5 ha area around the point in accordance with national forest definitions. For the drivers, one or more were registered for the same 2 km plot when observed together.

The survey form question template addresses the following hierarchical questions:

1. Is the point location forest or non-forest?
   a. If yes, what kind of forest?
   b. Is there a change between 2015–2020?
      i. If yes, what year (2016–2020) did the change occur?
      ii. Is it deforestation or degradation?
      iii. What drivers are observed in the 2 km plot around the point?
      iv. If no, end of survey.
   c. If no, what kind of non-forest?
      i. For certain types of non-forest (not agriculture or built-up) was regeneration observed during the time period?
   d. Any other information to note.

[16] https://collect.earth

Collect Earth Online results can be exported as a .csv (comma separated value) table with the coordinates and IDs of each points, along with columns for each of the questions, with responses in rows. These tables can be directly ingested into GIS or SEPAL.

Socioeconomic data collection

The approaches in this study are largely based on remote sensing. However, there is an important added value to be able to validate outputs of the analysis at the local level (namely through the collection of information from human surveys). This is important because it is technically not feasible to confirm forest disturbances that may have occurred long in the past or before the satellite record (particularly true for degradation); also, collecting information from local communities could provide much needed context for observed and perceived drivers, trends and the actors involved in forest change.

A set of interview and survey questions were developed to address the following:

2. What are the main proximate and underlying drivers of deforestation and forest degradation at the local level – in particular, those that cannot be seen from the satellite analysis?
3. What are the main uses of land that have been cleared of forest and/or reasons/products related to forest degradation – and what are the underlying driving forces behind them?
4. What role do local communities or smallholder farmers play in deforestation and degradation compared to external or large-scale actors (both within and beyond village boundaries)?
5. What drives and informs smallholder land-use decisions, particularly in relation to forest clearing and degradation behaviour?
6. What is the relationship between forest clearing and degradation, and household and smallholder demographics, livelihoods, and contextual variables?
7. What role do forest products and services play in rural livelihoods (such as employment, food security, energy, subsistence or cash income, cultural or spiritual significance, and health)?
8. How do local people perceive the availability, sustainability or changes in land use and forest resources?

For the purpose of this pilot project, two study sites were specifically selected in locations that were identified as having significant forest change according to the 2015–2020 spatial analysis, representing diverse contexts (such as transboundary areas and protected areas) with the presence of at least one of the proximate drivers of forest change identified in the satellite analysis and validation.

Ten facilitators were trained to collect data from local communities using village surveys, household surveys, focus group discussions, participatory mapping exercises, and key informant interviews. The first mission took place in Dja-et-Lobo, Cameroon in June 2022; the second took place in South Kivu, Democratic Republic of the Congo in July 2022.

For the pilot phase, a minimum of two villages were randomly selected within each site, based on the presumption that all villages in a study site are exposed to at least one of the proximate drivers of forest change listed in the previous section. Within each village, a minimum of 30 households were randomly selected (simple random sampling) for surveying. Enumerators were selected and trained to use digital survey tools developed using Collect Earth Mobile running on Android tablets. Four different surveys targeting specific groups were produced (Table 9).

Table 10. Four interrelated data collection modules used for local-level socioeconomic analysis of proximate and underlying drivers of forest change in Central Africa

1) Village survey (VS)	Conducted at the beginning of the fieldwork but revisited at the end to check and correct answers based on what is learned during the rest of the fieldwork. The aim is to collect objective village-level data that is common to – or with little variation among – all households, including the following village-level variables: geographic; demographic; infrastructure; land categories: area, users, main products and services; forest-use regulations and rules; risks and crises; and wages and prices. The information can be obtained from a variety of sources (depending on local context), including by the enumerator's own observation and measurement, secondary data (such as village records, project reports or other publications), or consulting village officials in cases where reliable written records are not available.
2) Focus group discussions (FGD)	Gender-separated focus group discussions are conducted prior to the household survey to collect contextual, qualitative data about village-level issues that affect all households. A semistructured approach guided by a skilled moderator or facilitator will use a combination of structured and open questions to promote discussion related to the topic at hand and elicit community perspectives, opinions, perceptions, understanding and knowledge, or feelings. Observations of participant interactions can help understand differences in perspectives and what factors influence opinions or behaviour. Topics include: village history and timeline, participatory village map, most important livelihood activities and income, seasonal calendar, agriculture and forest products, forest services, forest cover change and forest management, mining, infrastructure, biofuels, and conflict. This information informs the efficient implementation and quality of data of the household surveys.
3) Household surveys (HhS)	Structured household surveys are conducted to collect qualitative and quantitative data that is specific or unique to each household, including: household demographics, assets, livelihood activities and outcomes (off-farm, crop, livestock, forest, other); forest management activities (clearing, planting, protection); risks and vulnerability; and perceptions of forest change and sustainability. Aggregated household data are triangulated with the village survey and focus group discussion data and will be used to inform the key informant interviews.
4) Key informant interviews (KII)	Semistructured key informant interviews are conducted after the village and household-level data collection is completed, when the specific local land use and livelihood activities are known (customized for each village). They should be conducted with relevant and knowledgeable government officials at different levels (from local to national levels, as needed) with experts from non-governmental organizations, civil society organizations, researchers, etc. Interviews of key informants will collect data about the direct and/or indirect drivers of deforestation and degradation from beyond village boundaries that is directly related to the land use and livelihood activities of the local people (such as land clearing for commodity crop cultivation and artisanal mining) or indirectly related (such as conflict, infrastructure, large-scale mining, agriculture or forestry operations). Secondary data could also be used.

Results from Central Africa

The following results were produced from the pilot study in Central Africa.

Image composites

The following image composite products were produced as inputs into baseline data development and are available as Google Earth Engine assets[17] or may be reproduced in SEPAL.

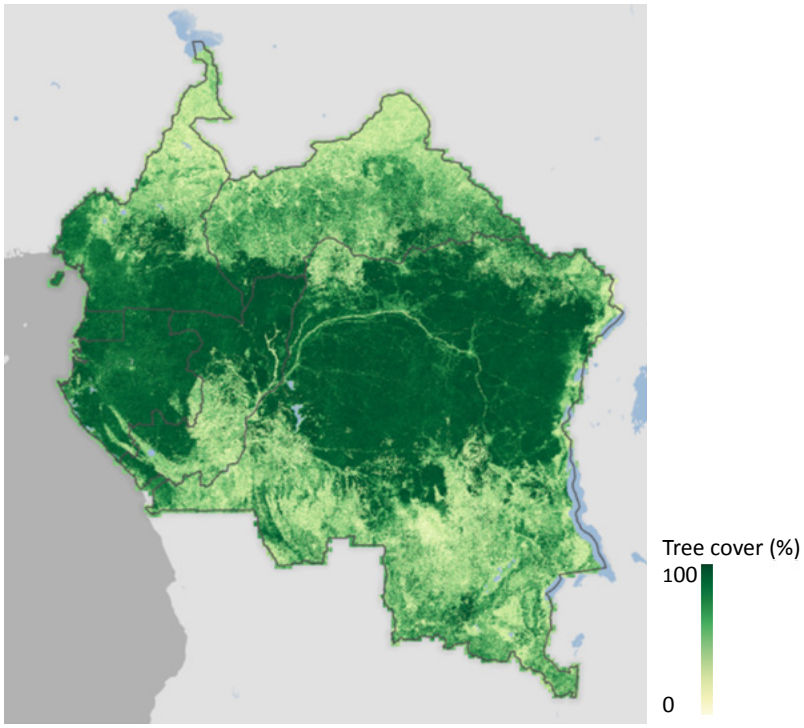
Table 11. List of composite products

Mosaic	Data Source	Criteria	Link to Module
Optical baseline	Landsat 4, 5, 7 and 8	1 January 2012–31 December 2015 with priority scenes selected with higher normalized difference vegetation index (NDVI), moderate cloud masking, no cloud buffer, surface reflectance and bidirectional reflectance distribution function (BRDF) correction, with medoid compositing.	Optical mosaic recipe in SEPAL
Radar mosaic	ALOS PALSAR	2015 mosaics provided by Japan Aerospace Exploration Agency (JAXA) with Quegan filter applied, rain forest degradation index (RFDI) index and masked texture parameters.	ALOS Kyoto & Carbon (KC) Mosaics module in SEPAL

Percentage tree cover

The percent tree cover map shows a continuous estimate of tree cover between 0 and 100 percent for the entire study region. We observe large areas of low tree cover (20 percent) where open savannahs are present in the north and south of the region. There is a large continuous block of high tree cover (80–90 percent) representing the central tropical forest belt.

Figure 11. Percent tree cover for the entire study region

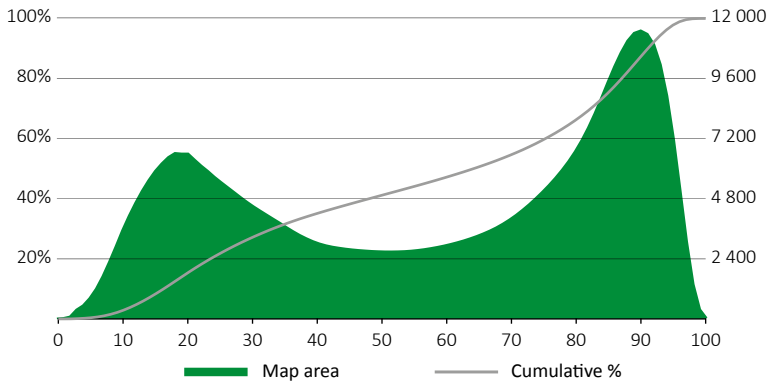


Note: Derived from multiple resolution analyses. Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Authors' own elaboration created in: GEE. 2025. GEE. https://earthengine.google.com. Map created in: ESRI. 2012. ArcGIS Pro. Version 3.5.2.

[17] https://data.congo.dddafrica.info

Figure 10. Area distribution and cumulative percentage of tree cover

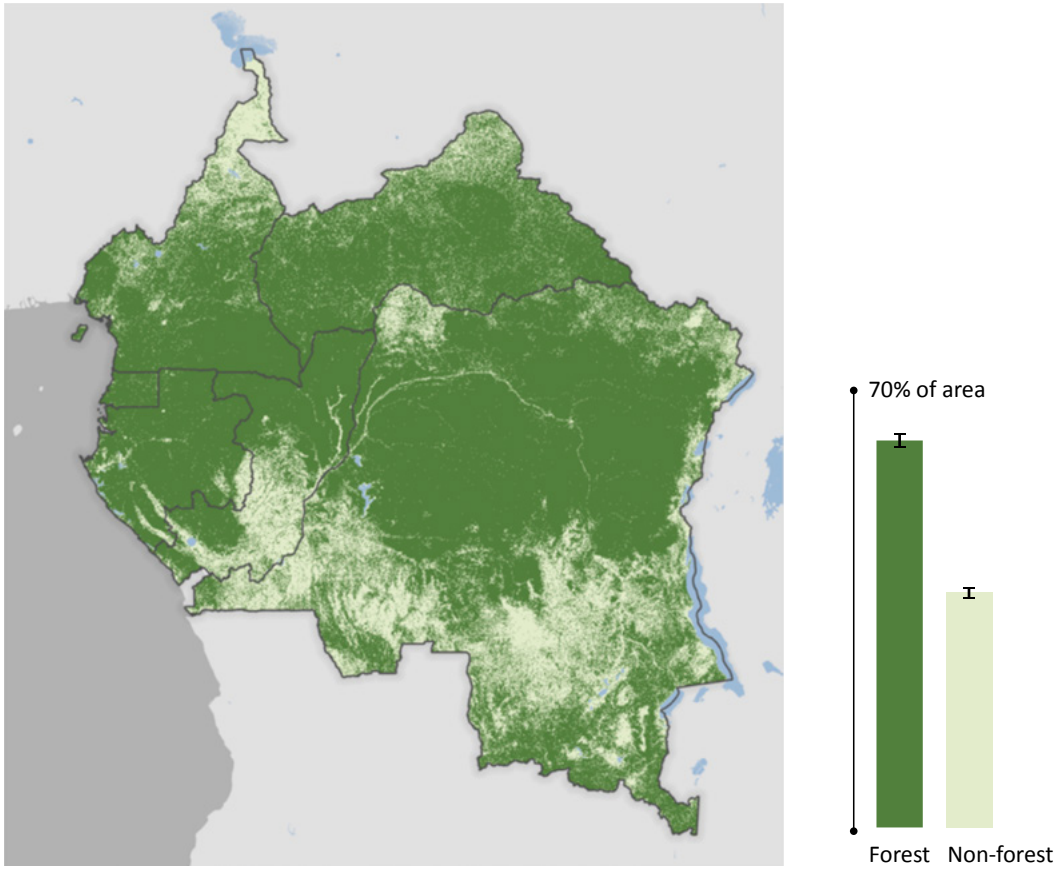


This information can be used to apply the area and canopy cover of national forest definitions for consistent mapping.

Forest/non-forest map

The forest mask was created by recoding values from the land cover classification estimates over 60 percent of the land area as forest. This includes all forest types, from tropical dense to dry open vegetation, more commonly found in Cameroon and the Central African Republic.

Figure 13. Forest mask for Central Africa



Note: Created by recoding the land cover map according to Table 6. Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Authors' own elaboration created in: GEE. 2025. GEE. https://earthengine.google.com. Map created in: ESRI. 2012. ArcGIS Pro. Version 3.5.2.

Overall accuracy of the forest mask is 71.14 percent, with higher commission errors than omissions, indicating that the classification tends to overestimate forest area. The sampling-based area estimates a total of 247.8 +/- 3.65 million ha of forest cover over the Central African region (approximately 61.2 percent of total land area).

Table 12. Accuracy assessment of forest/non-forest map (area adjusted)

Class	Producer accuracy	User accuracy	Omission error	Commission error
Forest	88.37%	71.34%	11.63%	28.66%
Non-forest	43.92%	29.49%	56.08%	70.51%

Table 13. Adjusted forest and non-forest area

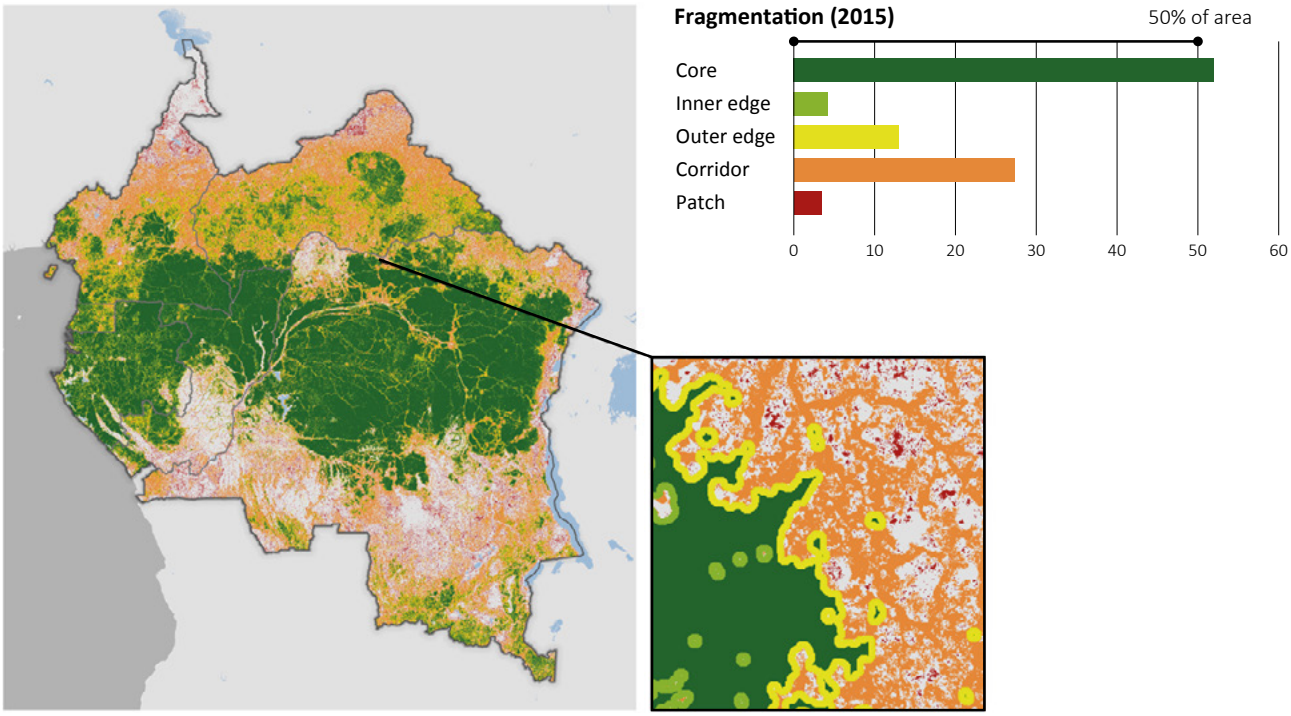
Class	Map Area (ha)	Adjusted area	+- CI (ha)	Adjusted area (%)	+-CI (%)	Lower CI	Upper CI
Forest	306 978 069	247 810 144	3 650 564	61.2%	0.90%	244 159 580	251 460 708
Non-forest	97 718 984	156 886 908	3 099 285	38.8%	0.77%	153 787 623	159 986 194

According to the validation data, the forest mask tends to overestimate forest area, particularly in the northern dry forests of Cameroon and the Central African Republic, which are generally dry open forests and commonly difficult to identify as forest over a gradient of tree cover.

Fragmentation

Out of the total forest area mapped, 52 percent are core intact forests, 4.2 percent and 13 percent are inner edge and outer edge, respectively, 27.4 percent are corridor forests, and 3.4 percent are small patches or islands (Figure 11). A large intact forest block extends throughout the tropical forest zone in southeast Cameroon, the Congo, the Democratic Republic of the Congo and Gabon, with several large contact patches in central Cameroon and the Central African Republic.

Figure 14. Forest fragmentation map for the baseline year, 2015



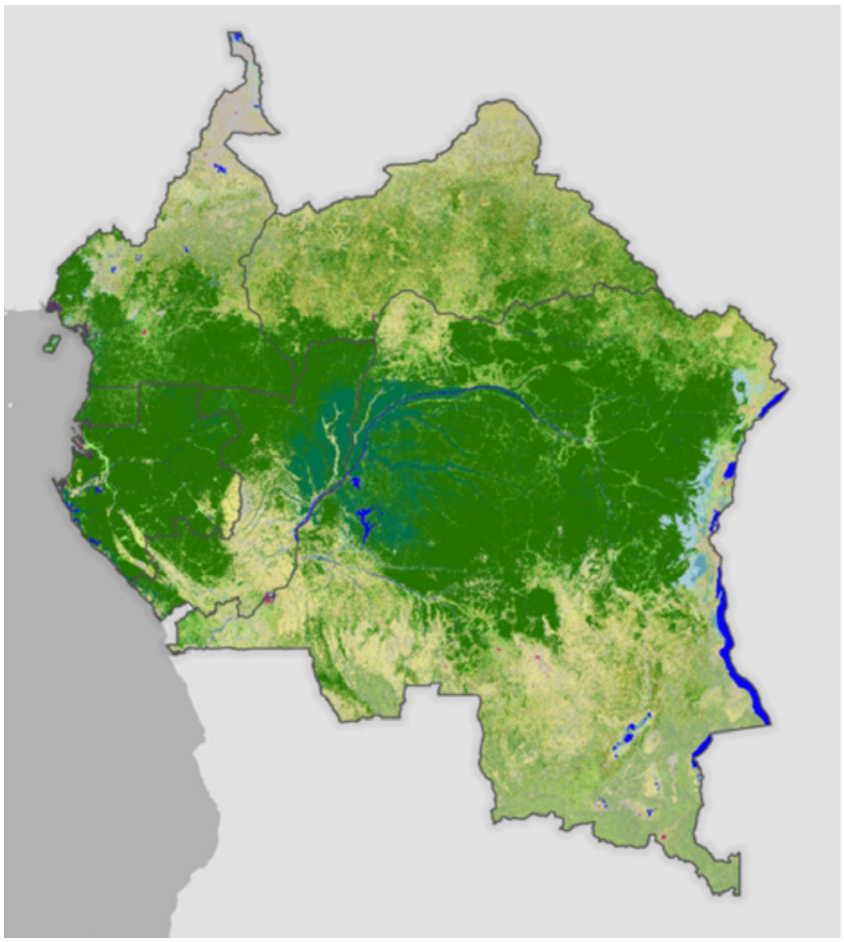
Note: Central African forests are comprised of a large continuous core forest covering more than half the study area. The inset shows how core forest can be perforated creating inner edges, and outer edges transition to fragmented corridor forests and small isolated patches. Refer to the disclaimer on page ii for the names and boundaries used in this map.

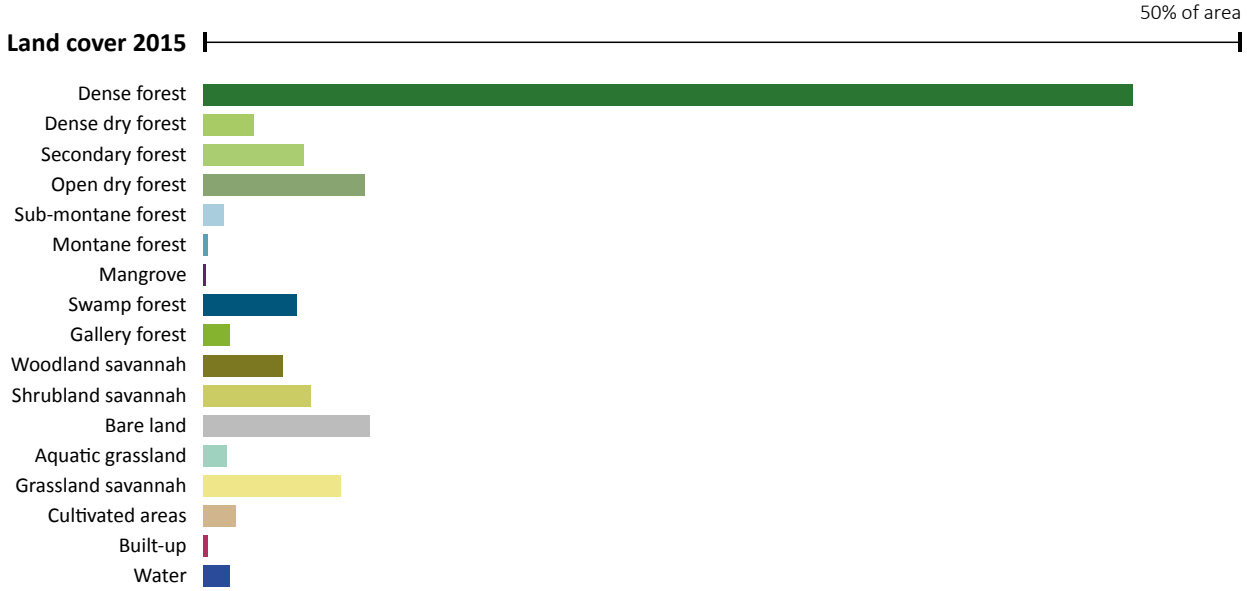
Source: Authors' own elaboration created in: GEE. 2025. GEE. https://earthengine.google.com. Map created in: ESRI. 2012. ArcGIS Pro. Version 3.5.2.

Land cover

The most common class of forest is dense tropical forest, covering nearly 180 million ha and extending over the central belt of the study region. Dry open forest is the next most common class, followed by secondary forests.

Figure 15. Vegetation and land cover for the Central African study region with relative size of classes, 2015





Note: Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Authors' own elaboration created in: GEE. 2025. GEE. https://earthengine.google.com. Map created in: ESRI. 2012. ArcGIS Pro. Version 3.5.2.

Figure 16. Total area of each forest type, the distribution of fragmentation classes and average above ground biomass

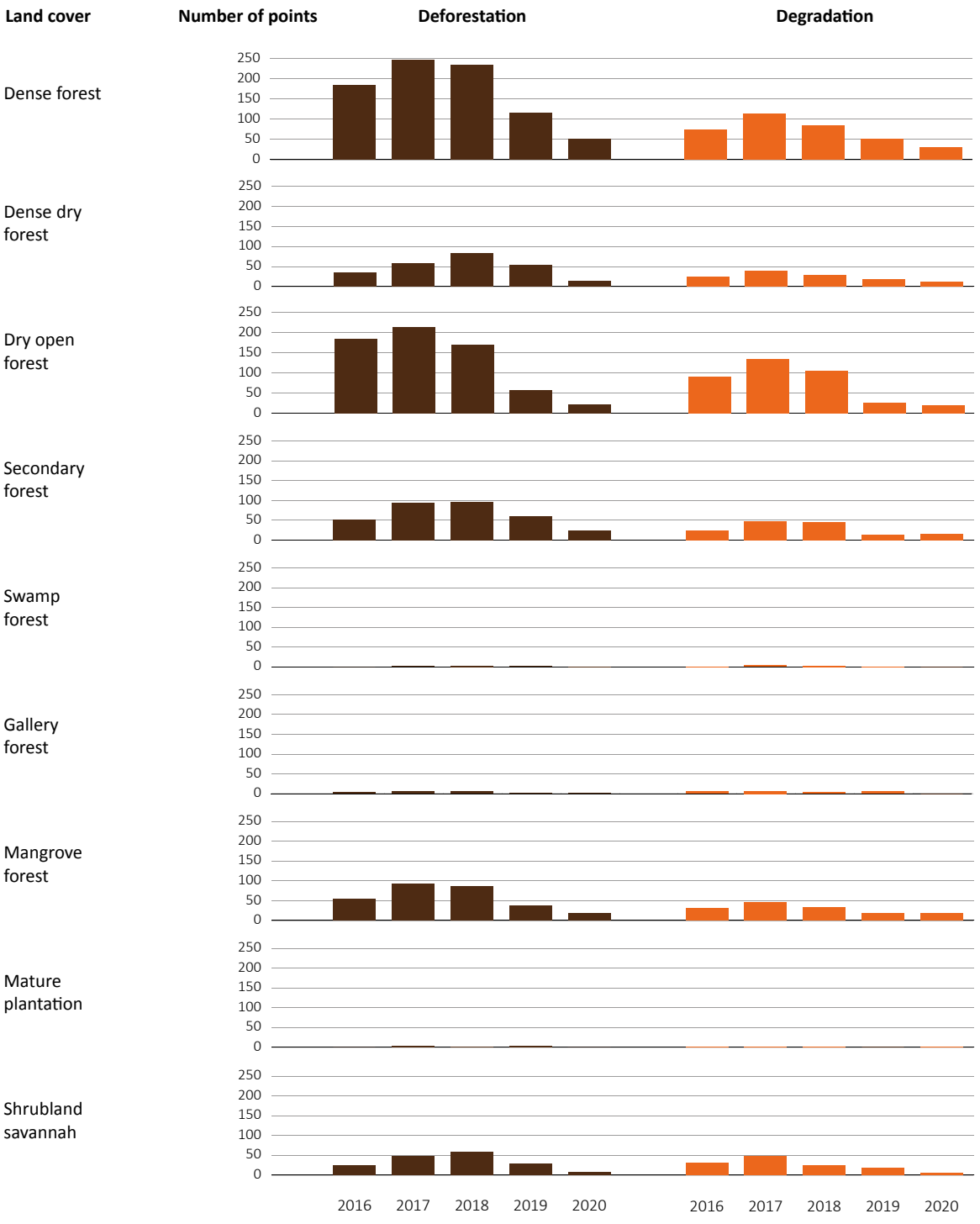
Note: The standard deviation of biomass per class is shown by the dotted lines.

As described in Shapiro *et al.* (2016), carbon stock steadily decreases with fragmentation, which is observed for all forest types. The large dense forest class is not only the most common, but largely intact and has the greatest above ground carbon stock. Swamp and sub-montane forests are also largely intact and store a higher amount of carbon relative to other vegetation.

Forest disturbances (2015–2020)

The visual interpretation of stratified randomly selected points (N[19] = 12 060) shows that changes are primarily observed in dense forest, which is the most common forest type (see Figure 15), followed by secondary forest. Overall, the number of changes observed have appeared to be decreasing since 2017.

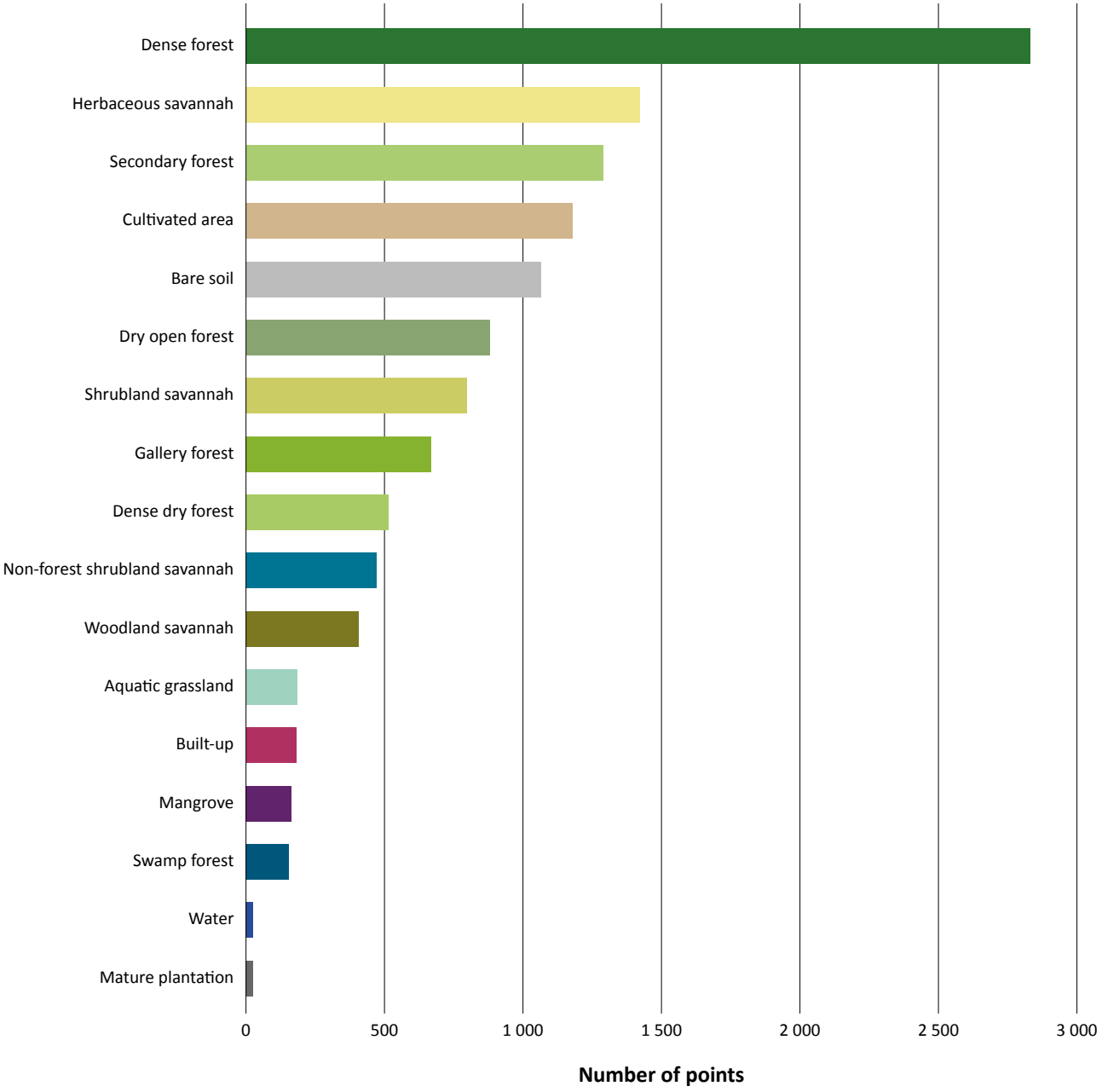
Figure 17. Summary of Collect Earth Online validation data showing forest class, type of change and date of change



[19] *N* refers to sample size.

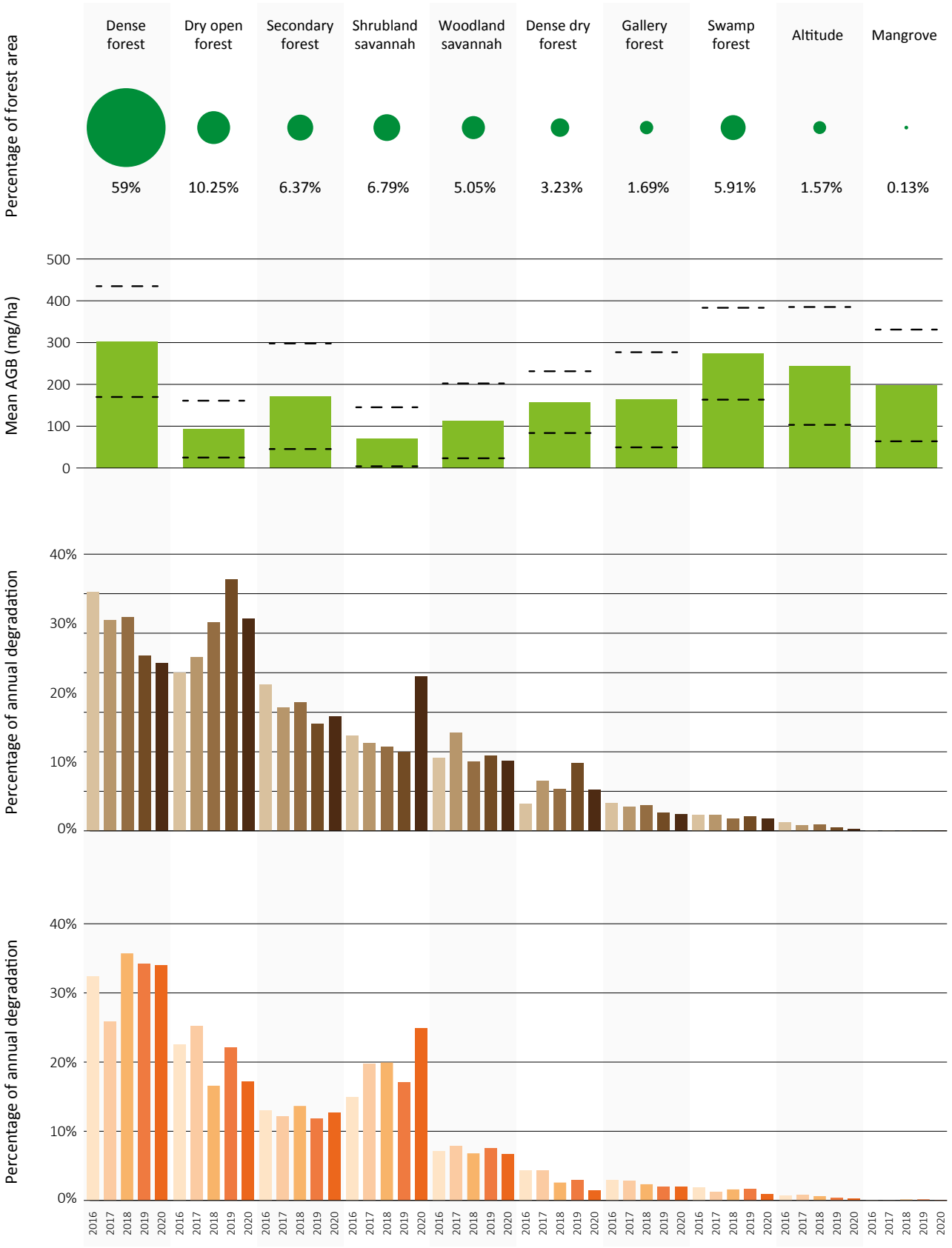
The distribution of land cover classes shows dense forest and herbaceous savannah to be the most common forest and non-forest land cover classes, respectively.

Figure 18. The distribution of stable and non-forest types in the visually interpreted dataset



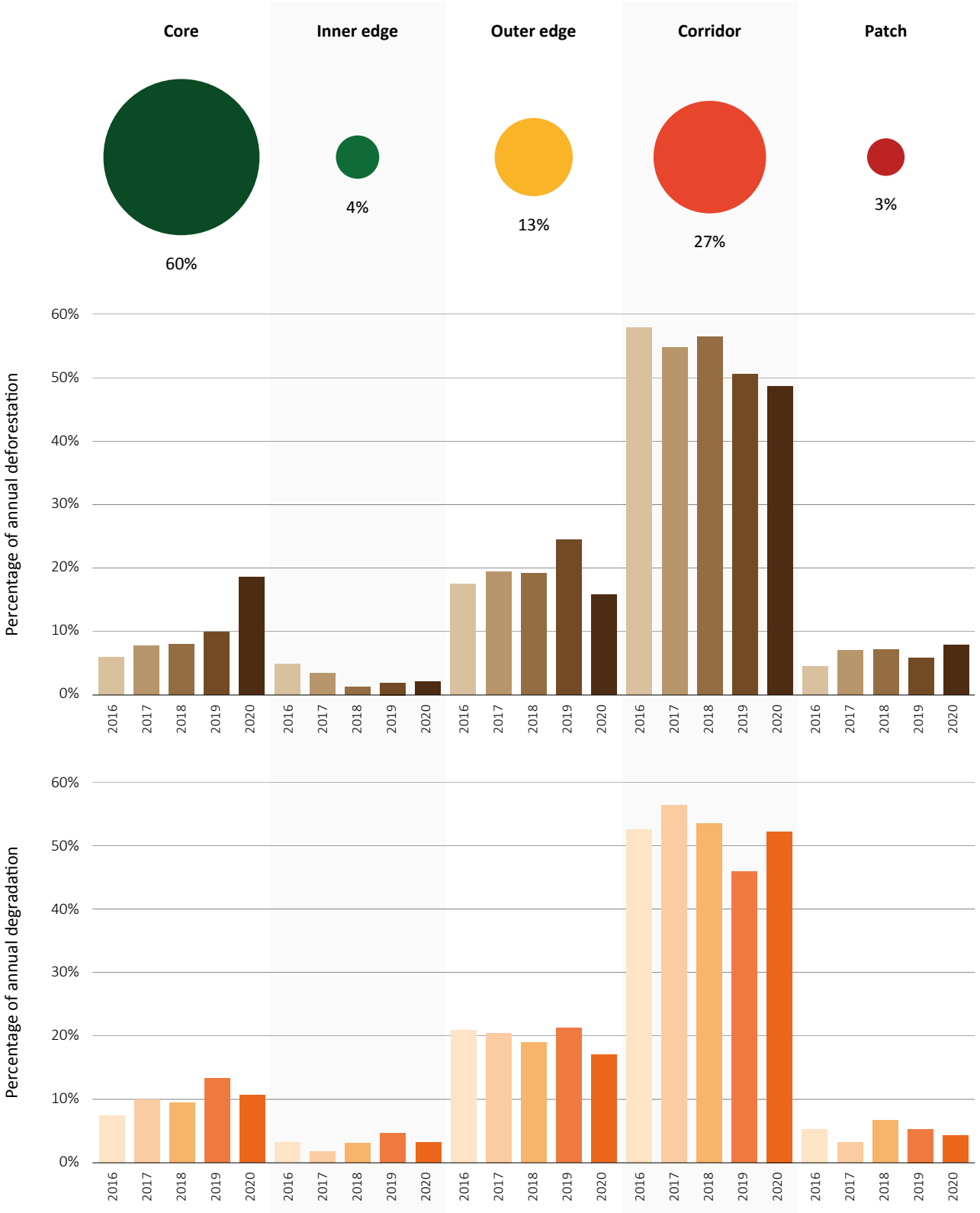
Carbon storage and fragmentation is relevant to accurately discern deforestation, degradation and stable areas from time-series analyses through the setting of thresholds on change magnitudes. Based on the visually interpreted data, higher biomass forest types (dense forest, swamp and mangroves) tend to have more stable annual dynamics than seasonal and deciduous forests.

Figure 19. Annual distribution of deforestation and degradation by forest type



In terms of changes by fragmentation class, all forest types experienced the most change in the corridor class, which has the lowest average biomass, except after patch forest.

Figure 20. Annual change by fragmentation class

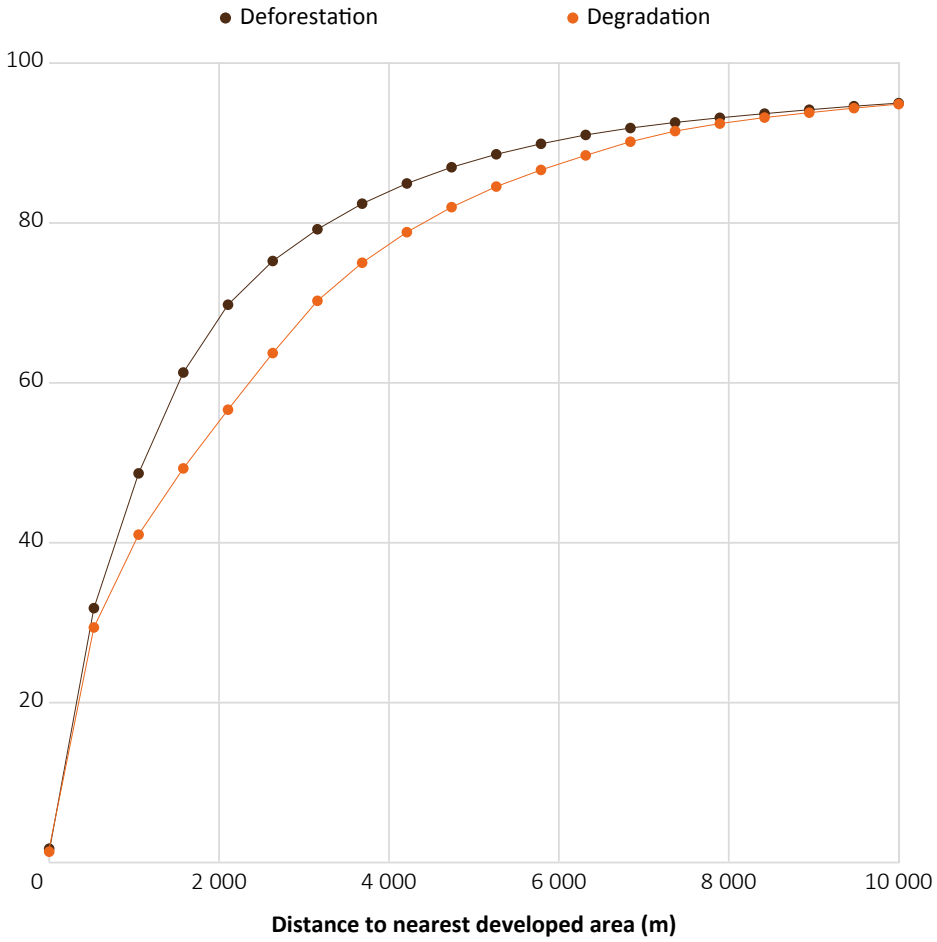


Note: All forest types combined. Top row shows the percentage of all regional forest in the fragmentation class.

Drivers assessment

This study confirms that most of the observations of deforestation and degradation are anthropogenic by assessing forest disturbances with respect to human presence, infrastructure and accessibility. We observed that about 80 percent of all deforestation is located within 3 km of the nearest road or settlement (Figure 19); in contrast, degradation generally extends slightly further, with 80 percent of degradation occurring within 4 km of the nearest road or settlement.

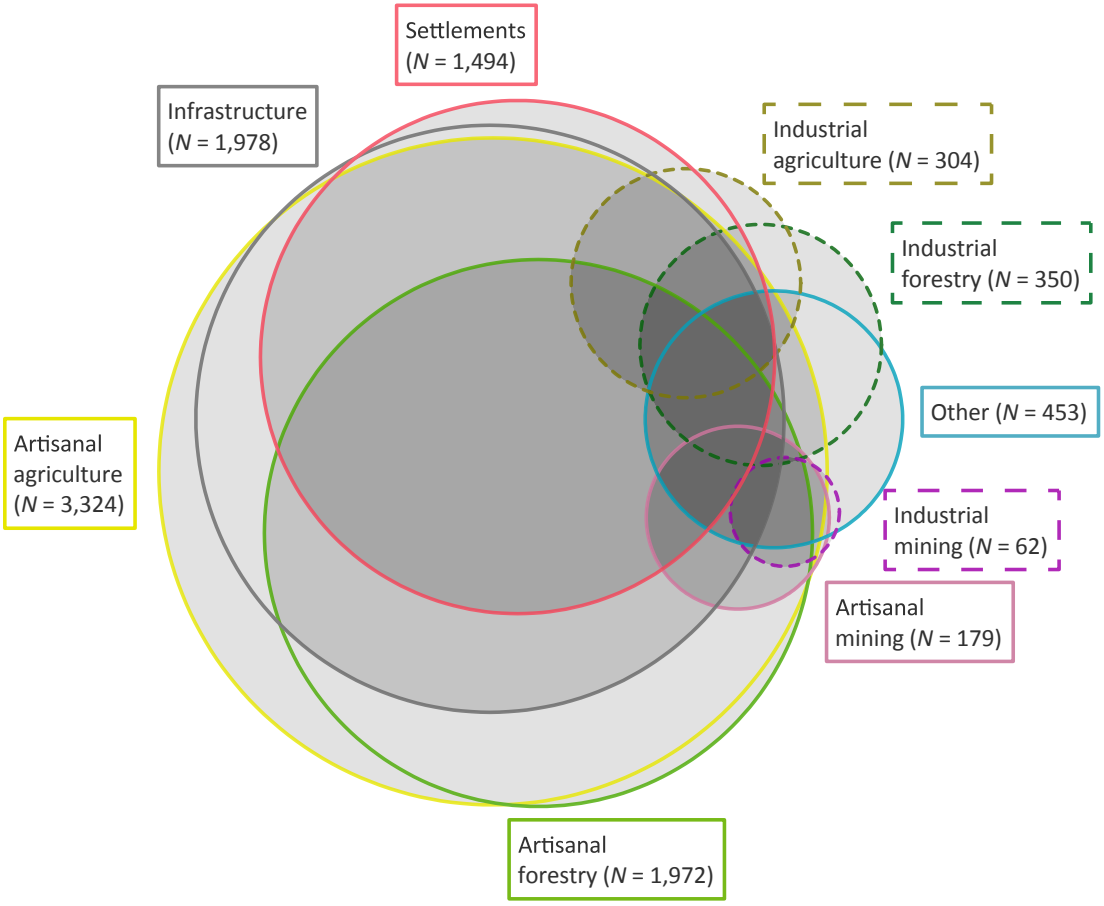
Figure 21. Cumulative proportion of deforestation and degradation relative to distance to nearest road or settlement



The presence of one or more direct drivers in plots located around areas of deforestation and degradation was quantified for the region. Of all plots with identified forest disturbance (*N* = 3 811), the most commonly observed driver was artisanal agriculture, followed by infrastructure, artisanal forestry and settlements (Figure 20). A majority of plots have more than one driver observed, with only 20 percent of all change plots with a single driver identified. The most common number of drivers is two (*N* = 1 018), followed closely by three (*N* = 1 006).

The four most common drivers are also commonly observed together, while certain drivers never overlap. For example, industrial mining is only found with few of the other drivers and is never observed with industrial agriculture.

Figure 22. Diagram representing the overlap and frequency of observed drivers


Settlements (N = 1,494)
Infrastructure (N = 1,978)
Industrial agriculture (N = 304)
Industrial forestry (N = 350)
Other (N = 453)
Artisanal agriculture (N = 3,324)
Industrial mining (N = 62)
Artisanal mining (N = 179)
Artisanal forestry (N = 1,972)

Note: *N* is the number of visually interpreted samples.

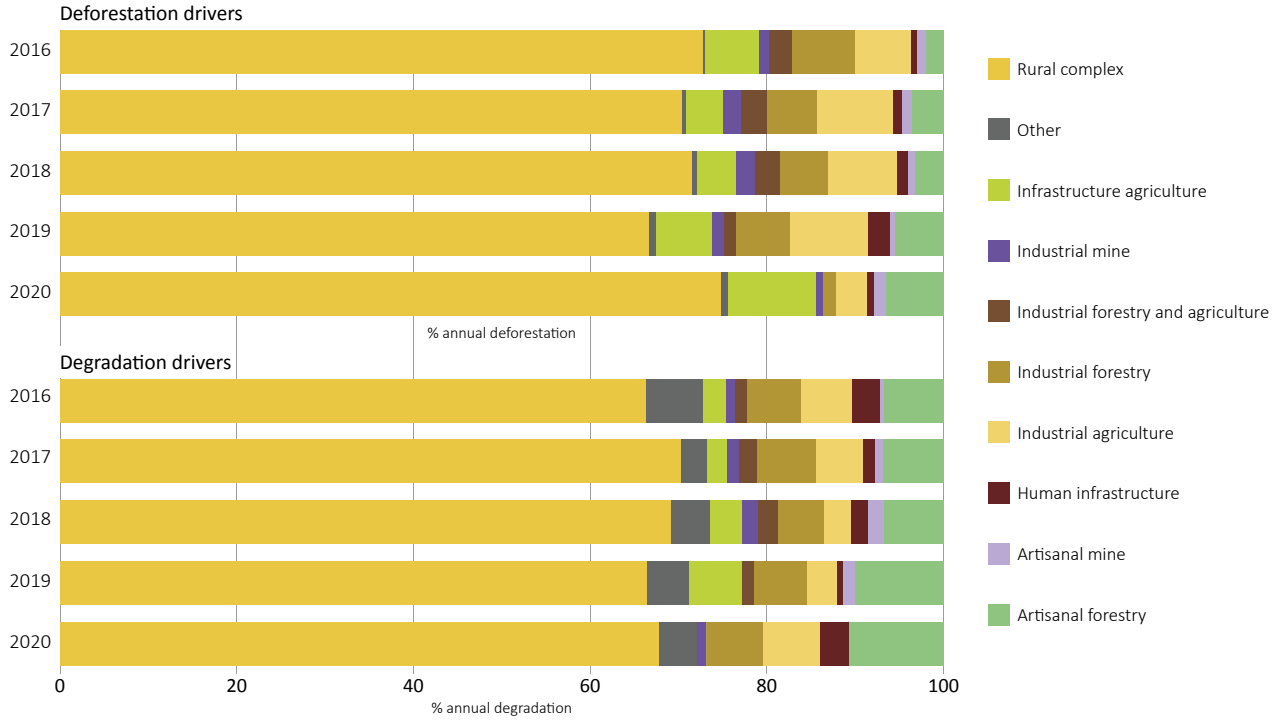
To address the overlap of drivers and interpret local context, our approach identifies archetypes (common driver combinations), which represent realities and processes on the ground (Table 13). The most common archetype consists of four drivers – artisanal agriculture, artisanal forestry, roads and settlements – representative of the agricultural mosaic (so-called rural complex) commonly observed in the region (Molinario *et al.*, 2020).

Table 14. Observed combinations of drivers were grouped into thematic classes or archetypes

Archetype	Drivers	Numbers of samples
Rural complex	Artisanal agriculture with settlements, with or without roads or artisanal forestry, and no industrial drivers	2 607
Industrial agriculture	Industrial agriculture and other non-industrial drivers	253
Infrastructure-related agriculture	Infrastructure and artisanal agriculture observed together	237
Industrial forestry	Industrial forestry and other non-industrial drivers	223
Artisanal forestry	Artisanal forestry with or without "other" driver, with or without settlements or roads, without any artisanal agriculture or industrial drivers	187
Industrial forestry and agriculture	Industrial forestry and industrial agriculture identified together	84
Industrial mining	Presence of industrial mining	59
Human infrastructure	Roads or settlements observed alone or together, no other drivers present	56
Artisanal mining	No more than two drivers, including artisanal mining, no industrial drivers present	37

We assess these archetypes in space and time, presented as relative weight, similar to Hosonuma *et al.* (2012). The rural complex has the largest contribution to deforestation and degradation in all years: over 75 percent of identified deforestation and 70 percent of forest degradation. The relative contribution seems to have been decreasing until 2019, while the contribution to degradation is relatively stable over time. The presence of artisanal forestry (observed alone) and agriculture associated with infrastructure are increasing over time. There are similar trends for degradation, of which artisanal forestry has a greater contribution than for deforestation. Industrial drivers related to forestry, agriculture and mining are generally observed to be stable or decreasing.

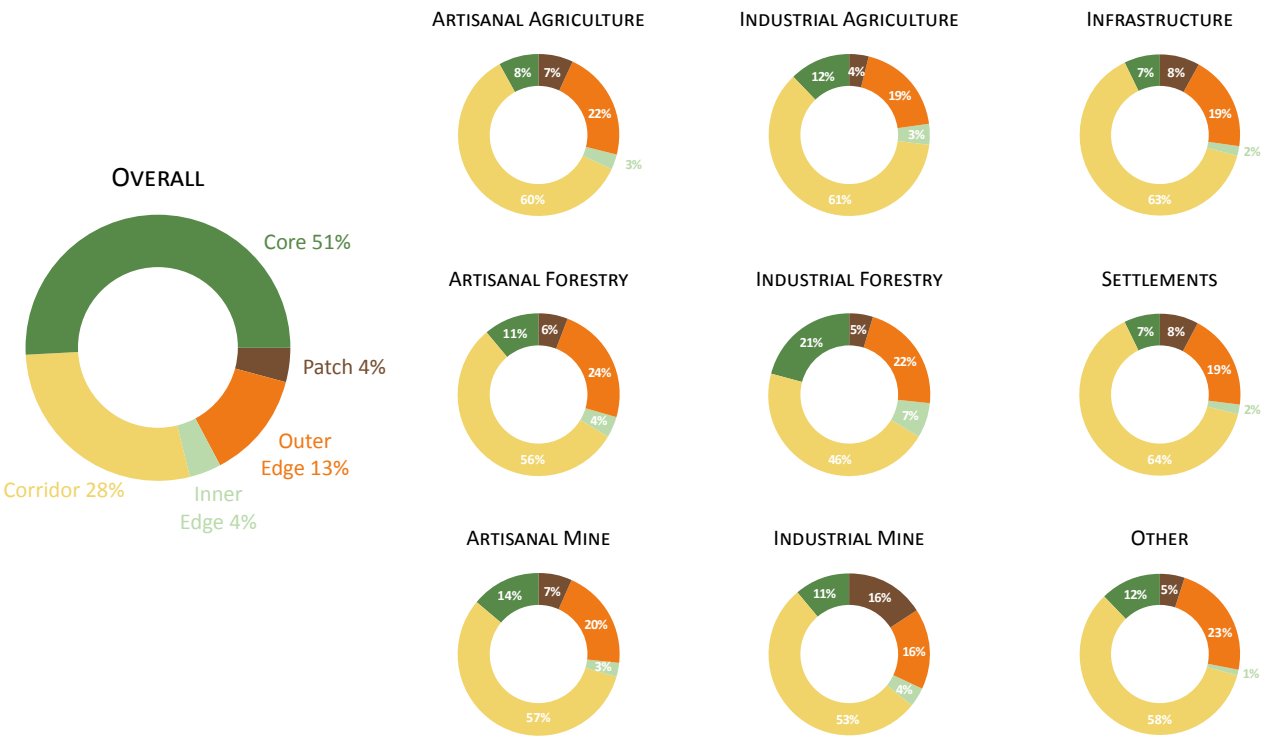
Figure 23. Grouped deforestation and degradation drivers, 2015–2020



Note: Time shown by relative contribution to annual deforestation and degradation.

Each archetype was also assessed in relation to fragmentation class. We estimate the overall distribution of fragmentation classes over the entire study region (Figure 21), and the proportion of each class associated with each archetype. Although most forests are in the intact core class, and only about one quarter are corridors, all drivers are disproportionately affecting fragmented forests, albeit differently. Industrial activities such as forestry and agriculture affect core forests more than other drivers, along with artisanal mining and forestry.

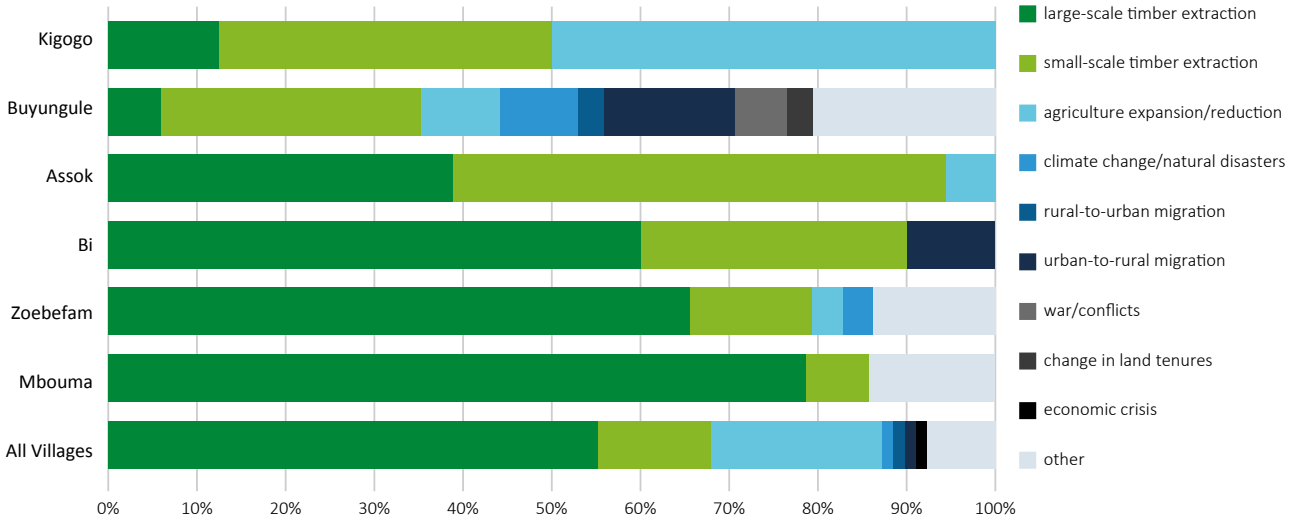
Figure 24. Presence of driver archetypes in different forest fragmentation classes



Socioeconomic survey data

Within and surrounding the villages which were targeted for socioeconomic data collection, the industrial exploitation of natural resources and infrastructure development seemed to pose the largest threat to forests and biodiversity according to local perspectives. Loggers were present in all villages visited, including industrial, state-authorized loggers, as well as small-scale or illegal operators. In the Democratic Republic of the Congo, mining operations both industrial and artisanal are also increasing their impacts. Infrastructure development is also a significant driver, particularly in Cameroon, where road construction directly impacted forests and opened previously inaccessible areas to agriculture development, illegal poachers and loggers. Industrial mining and associated hydroelectric dams seem positioned to become a leading driver of deforestation and forest degradation in several of the areas visited.

Figure 25. Household perspectives



The missions conducted in Cameroon and the Democratic Republic of the Congo suggest that the communities surveyed are practicing a broadly sustainable system of land management. A majority of their land use is located within dense tropical forests where they fish, hunt, collect non-timber forest products and conserve for cultural purposes, while agricultural activities are primarily occurring in secondary forests.

Most households practice a traditional system of rotational agriculture where small plots are cultivated while leaving other areas to regenerate for future cultivation (fallow areas). The distance to agricultural areas and area use differ by village (Figure 23 and Figure 24).

Figure 26. Average land area used by households in all villages surveyed

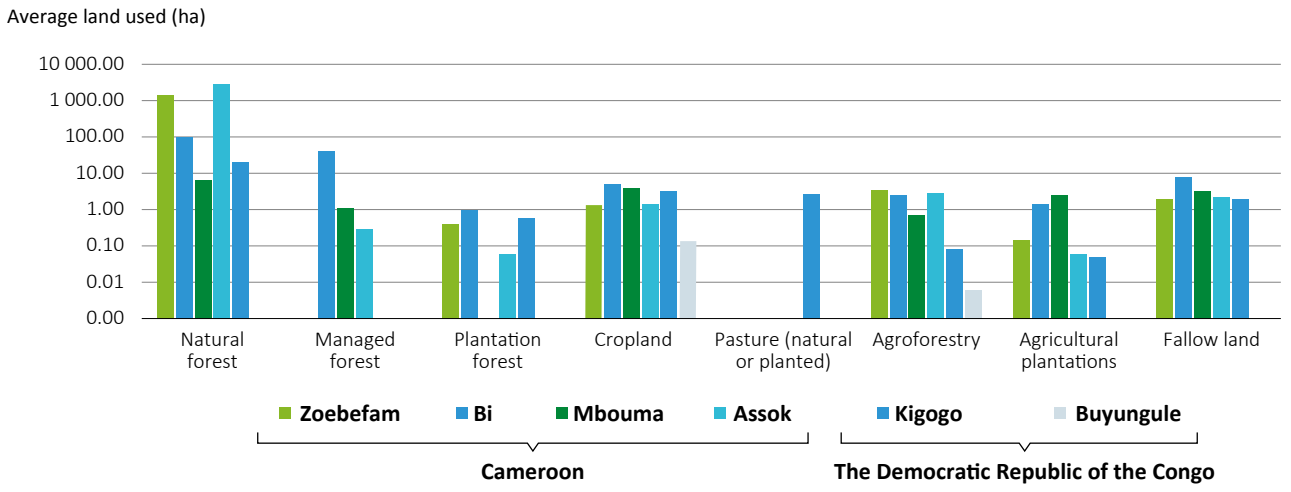
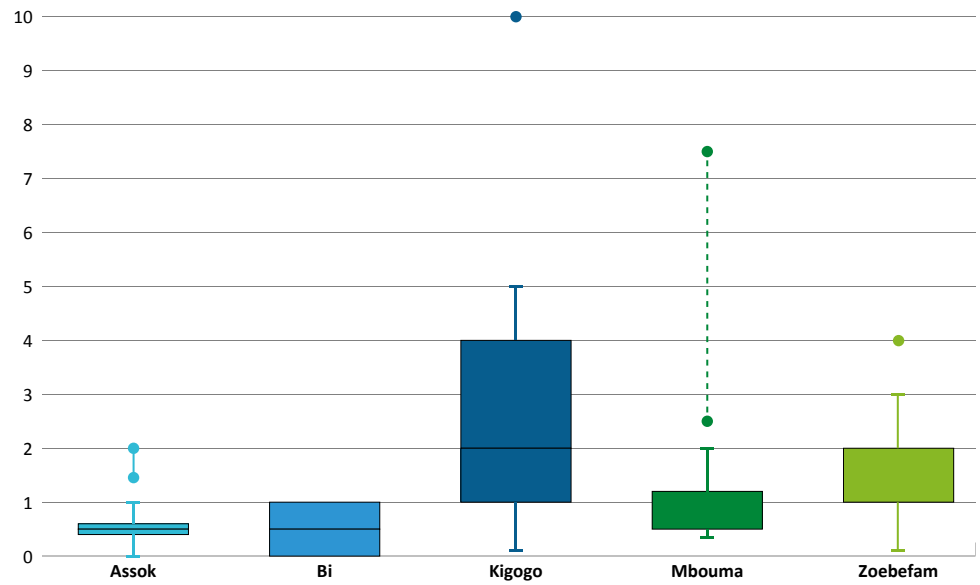


Figure 27. Distance to forest cleared by village



Note: Shows how local forest use is in some places relative to others.

Several community members in Cameroon cultivate shade-grown cocoa using traditional ecological knowledge. The households of Indigenous Peoples differ in that many are seminomadic and depend on collecting forest products more than farming. Out of 163 points collected on where communities carry out livelihood activities, none overlap with deforestation and only one overlaps with forest degradation. This indicates that small-scale community activities in forests may not be significant or persistent enough to be identified from satellite imagery, which reinforces the notion that overall, the impacts of small-scale agriculture may be less than expected. The traditional ecological knowledge of Indigenous Peoples and local communities should be further understood and leveraged to ensure that Central African rainforests continue to remain one of the most intact forest landscapes in the world.

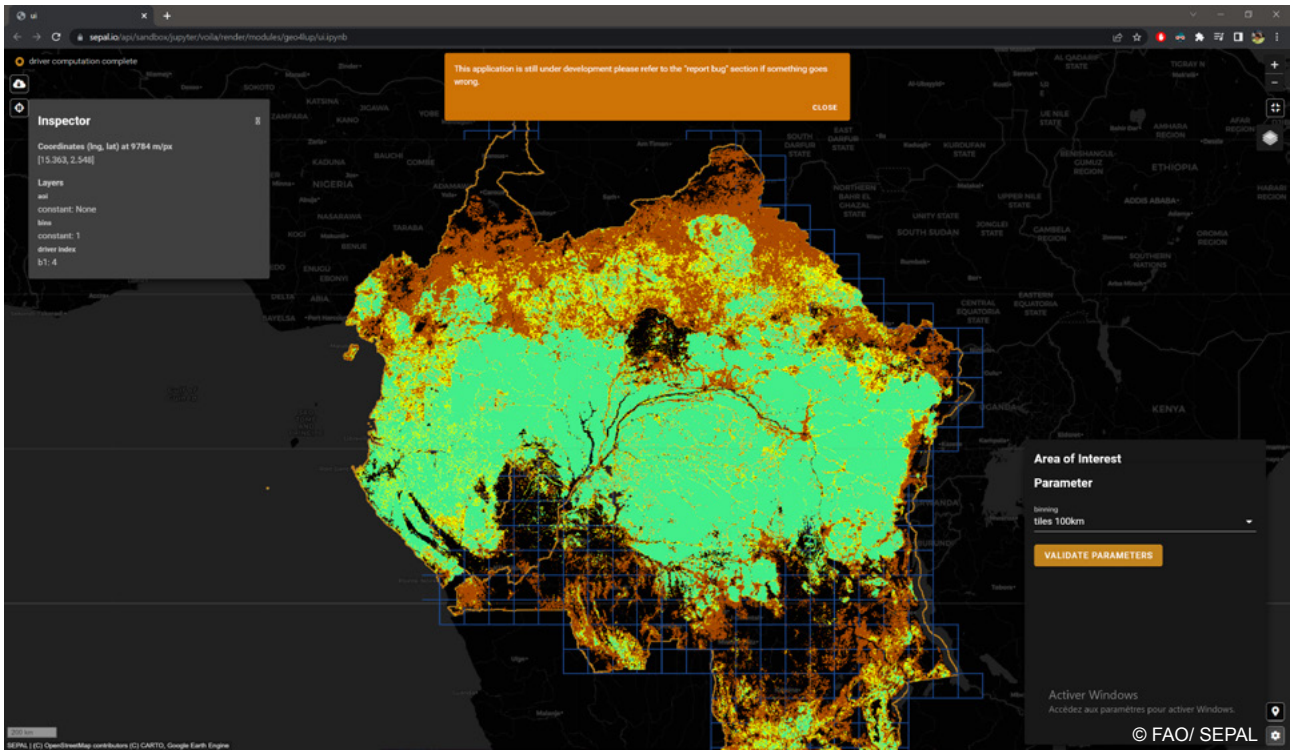
In addition to observing driver archetypes from remote sensing coupled with socioeconomic survey data to contextualize the project outputs, additional efforts aim to develop open-source cloud-based tools for specific practitioner use. The following section presents a use-case applying the validation dataset with parameters derived from socioeconomic surveys to support land-use planning.

Geo4LUP: Utilizing validation dataset and cloud-computing in the use-case of an open-source decision-support tool for land-use planning practitioners

Applying the Open Foris Solutions presented in Box 2 (particularly SEPAL and Google Earth Engine), FAO, CAFI and partners developed a practitioner-oriented, open-source tool for decision support in land-use planning as an exploratory use-case for the validation dataset on drivers of deforestation and forest degradation described in the section, Validation of change and drivers using Collect Earth Online, emphasizing the importance of driver archetypes such as the rural complex.

Geoinformatics for Land Use Planning (Geo4LUP) is a Google Earth Engine-based module for SEPAL, currently available in beta+ testing form, to be integrated within the existing ecosystem of SEPAL modules. The module supports decision-making and site selection in land-use planning by predicting and visualizing the risk of deforestation and degradation to intact forest resulting from proposed land-use modifications, such as road or artisanal agriculture expansion, enabling planners to make informed decisions about the expansion of economic and development activities in a proactive, risk-sensitive manner by selecting sites that pose fewer risks to intact forest.

Figure 28. Mock-up of Geo4LUP landing page in SEPAL



Notes: Refer to the disclaimer on page ii for the names and boundaries used in this map.

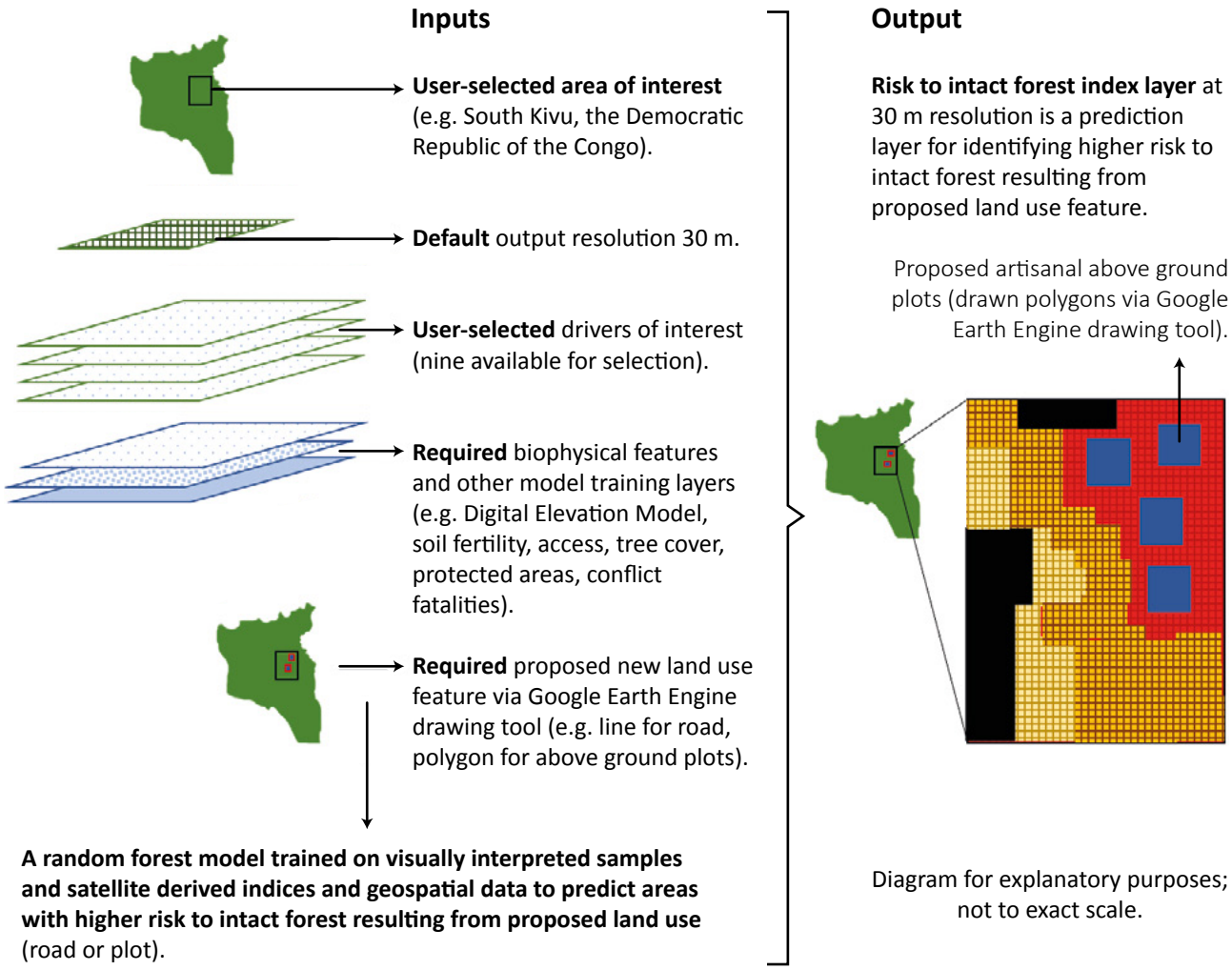
Source: Authors' own elaboration made in SEPAL (sepal.io)

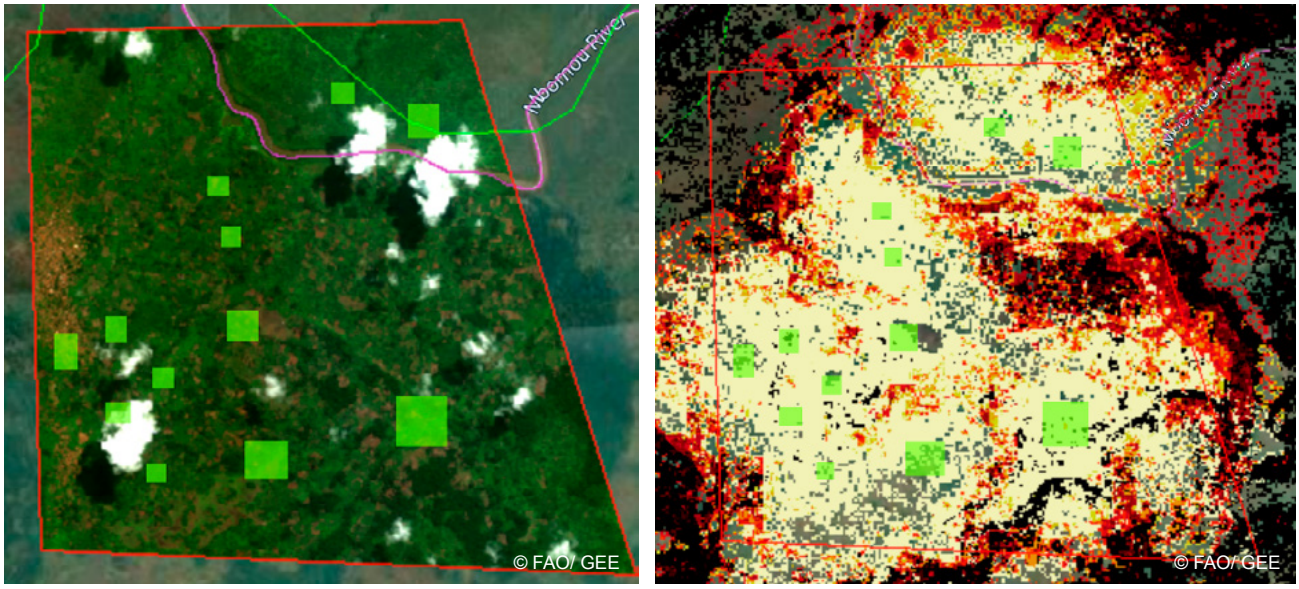
By using the drawing tool in Google Earth Engine, the user draws hypothetical road or agricultural plots in the module (with lines drawn to feature collection for proposed roads, and polygons drawn to feature collection for proposed agricultural plots).

The model then predicts where deforestation and degradation are expected to occur (high, medium and low risk, by likelihood that a deforestation and degradation event will occur) – based on the associated remotely sensed indices and biophysical, forest and driver data layers, trained by visually interpreted driver samples.

Finally, the output layer allows the user to identify areas around the proposed agriculture or road feature that are expected to produce the greatest or least risk to intact forest in terms of likelihood of a deforestation or degradation event. Employed for a demonstration, this model was used to determine the effectiveness of transboundary protected areas in conserving intact forest complexes in Central Africa and has implications for sustainable agriculture development and protected areas management (Bernhard *et al.*, 2024).

Figure 29. Inputs and output schematic for Geo4LUP, and a sample output


Inputs
User-selected area of interest (e.g. South Kivu, the Democratic Republic of the Congo).
Default output resolution 30 m.
User-selected drivers of interest (nine available for selection).
Required biophysical features and other model training layers (e.g. Digital Elevation Model, soil fertility, access, tree cover, protected areas, conflict fatalities).
Required proposed new land use feature via Google Earth Engine drawing tool (e.g. line for road, polygon for above ground plots).
A random forest model trained on visually interpreted samples and satellite derived indices and geospatial data to predict areas with higher risk to intact forest resulting from proposed land use (road or plot).
Output
Risk to intact forest index layer at 30 m resolution is a prediction layer for identifying higher risk to intact forest resulting from proposed land use feature.
Proposed artisanal above ground plots (drawn polygons via Google Earth Engine drawing tool).
Diagram for explanatory purposes; not to exact scale.



Note: Geo4LUP on left; sample output at 30 m resolution from the Google Earth Engine JavaScript user interface on right. The red outline is the site boundary, and the purple outline is a protected area boundary. Light green polygons are user-drawn hypothetical and/or proposed agriculture plots (approximately 1 ha). Dark red pixels indicate the highest predicted risk to intact forest from the hypothetical artisanal agriculture plots, while orange and yellow indicate medium and lower risk, respectively. Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Authors' own elaboration overlaid upon the Google Satellite basemap in GEE. Map created in: GEE. 2025. GEE. http://earthengine.google.com

Assessing direct drivers of forest disturbance in Central Africa

This global methodology was piloted in six countries of Central Africa to assess forest disturbance over 2015–2020 and quantify the associated direct drivers in both time and space.

Direct drivers of change

We provide the first assessment of direct drivers in the Central African study region for 2015–2020, addressing deforestation and degradation separately, as well as over time – essential for targeting management and interventions (Rudel *et al.*, 2009). The majority of deforestation and degradation is found near settlements or roads, which is expected, as forests are easier to access and clear (Hansen *et al.*, 2020; Wilkie *et al.*, 1998). This was further validated by socioeconomic surveys conducted in pilot landscapes. Other studies have explored the role of roads and settlements on deforestation inside forest concessions, an effect which can be counteracted with effective management plans (Tritsch *et al.*, 2020).

The dominant direct driver associated with deforestation and degradation is observed to be artisanal agriculture, which has a long history and tradition in the region (Geist and Lambin, 2002; Tegegne *et al.*, 2016; Tyukavina *et al.*, 2018). While it is not possible to determine from remote sensing if agriculture is only for subsistence, local surveys indicate that agricultural activities may also include the production of commodities for local markets; also, larger cities may draw resources often from nearby rural areas.

Market-based measures that some countries currently adopt or promote, which aim to reduce the pressure of agricultural supply chains on forests (deforestation-free supply chains), may therefore have very limited effects in the context of the Central African region, since the major driver (artisanal agriculture) is poorly connected to global markets.

The rural complex archetype, a combination of artisanal agriculture, forestry, roads and settlements without the presence of industrial activities, and the most commonly reported direct driver in other studies (Ickowitz *et al.*, 2015), is targeting fragmented forests; industrial activities such as mining, forestry and agriculture are observed to be less present overall and do not currently appear to be increasing, despite numerous reports and predictions (Tegegne *et al.*, 2016). While this archetype is the most common throughout the region, its potential impacts on carbon and biodiversity are likely much lower and less permanent than industrial agricultural activities, due to the lower intensity of activities and fallow periods that can allow for natural regeneration of vegetation (Karthik, Veeraswami and Samal, 2009), as well as its predominant presence in corridor and fragmented forests versus core forest ecosystems.

Small-scale agricultural activities tend to be localized around settlements, existing clearings (Molinario, Hansen and Potapov, 2015), and already fragmented forests, limiting the spatial extent of impact in intact, carbon-rich forests. Furthermore, with the larger increase in the area of cropland extent between 2015 and 2019 in areas that are non-forest (Figure 29) (Potapov *et al.*, 2022), there is an indication that non-forest or regenerating areas are preferred for the establishment of agriculture than intact forested areas.

The dominance of the rural complex is not surprising given the significant dependency of rural populations on agriculture, as well as its long history and links to culture and economy (Arthur-Josué, Faustino and Godfrey, 2020; Sonwa *et al.*, 2010). In contrast, we find that industrial drivers tend to be more present in core, carbon-rich forest types. Furthermore, industrial activities such as mining, while relatively limited in extent, may have more permanent and significant impacts on human health, carbon and biodiversity (Edwards *et al.*, 2014), which can be more difficult and costly to restore than letting small-scale agricultural areas naturally regenerate (Stanturf *et al.*, 2019). However, the contribution of the rural complex archetype to forest disturbance is potentially increasing with unsustainable agricultural practices and expected to expand with increasing population, which can lead to reduced fallow times and land degradation (Ickowitz *et al.*, 2015). There is a need for the improvement of rural agricultural practices, which are particularly vulnerable to climate change and can subsequently affect food security, health and livelihoods (Arthur-Josué, Faustino and Godfrey, 2020; Challinor *et al.*, 2007; Connolly-Boutin and Smit, 2016).

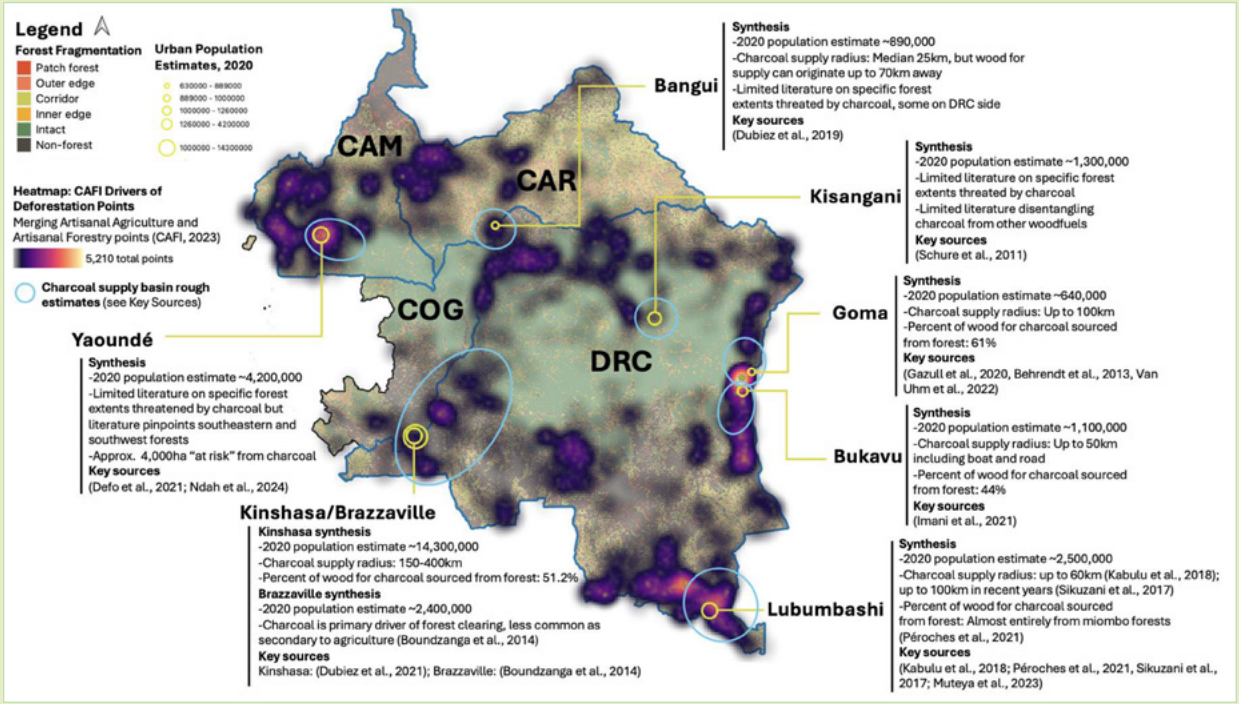
The central premise of our approach is the identification of multiple overlapping drivers, which is representative of deforestation and degradation occurring at national and subnational scales (Butsic *et al.*, 2015; Carr and McCusker, 2009; Ferrer Velasco *et al.*, 2020; Shapiro *et al.*, 2021a), as well as the result of the actions of multiple actors, processes and motivations (Moonen *et al.*, 2016; Rudel *et al.*, 2009; Rudel and Roper, 1997). Global assessments or post-disturbance land use cannot adequately discern multiple drivers (Ferrer Velasco *et al.*, 2020; Rudel *et al.*, 2009) and are not relevant for decision-making that requires national context (Tegegne *et al.*, 2016). Furthermore, drivers need to be considered beyond their spatial footprint: any direct driver of forest disturbance does not solely affect the direct area it covers, but inevitably influences what is around it which is particularly true for linear infrastructure such as roads (Ibisch *et al.*, 2016; Kleinschroth *et al.*, 2019), or industrial activities which inevitably incur changes outside permit boundaries, through connecting infrastructure or land clearing to support the livelihoods of local communities drawn to these areas (Molinario *et al.*, 2020). Agriculture that is not associated with infrastructure will tend to be used for subsistence activities, whereas agriculture along roads is better connected to markets, which increases the potential to produce for sale (Ickowitz *et al.*, 2015).

One specific driver absent from our conclusions is the extraction of fuelwood and harvesting for charcoal, which is being reported as a significant cause of deforestation and degradation in Central African countries and has the potential to increase (Behrendt, Megevand and Sander, 2013; Bilonda, 2020; Schure *et al.*, 2012). Access to electrical infrastructure is very limited in the study region, making populations entirely dependent on charcoal for preparing food (Behrendt, Megevand and Sander, 2013; Schure *et al.*, 2011). Large-scale harvesting of fuelwood is mostly driven by demand from urban centres, and is mostly informal and uncontrolled, although the importance of meeting energy needs and increasing prices are driving larger, more industrial forms of fuelwood collection in some countries (Schure *et al.*, 2012). Within our methodology, we lack specific information to be able to identify the scope and impact of such practices (Molinario *et al.*, 2020). The artisanal forestry driver definition includes the harvesting of such forest products, and we observe a consistent increase over the time period, particularly associated with degradation; however, we cannot discern from satellite for what purpose forests are being degraded. The 5 m resolution of Planet imagery, which is the only high-resolution source consistently available throughout the study period, limits the collection of specific and robust evidence to identify charcoal production, such as the presence of kilns. Given the increasing scale of these activities, they could in fact be large enough to be identified as industrial forestry according to our definitions (Uhm, Tjoonk and Bakole, 2022). Additional research, including socioeconomic surveys, which are currently underway, are necessary to understand the scale of this driver in more detail.

Box 1. Charcoal production as a driver of deforestation and degradation in the Congo Basin

Charcoal demand and production techniques have been implicated as drivers of forest degradation, and are associated with primary drivers of deforestation, across forests of Sub-Saharan Africa including Central Africa's Congo Basin forests. However, understanding the magnitude of deforestation and degradation directly attributable to charcoal can be methodologically challenging, as charcoal may be primary driver of forest clearing in some locations, but in others, charcoal may be a secondary product of forest clearing for other reasons such as conversion to small-scale agriculture. FAO and CAFI conducted an additional study in 2024 to synthesize both English and French literature related to the forest implications of charcoal demand and production for Central Africa's Congo Basin, consolidating evidence regarding the magnitude of threat that charcoal poses to the Congo Basin forests. Using n=68 studies (n=30 in English, n=38 in French) of the charcoal-deforestation nexus relevant to the Congo Basin forests, our synthesis systematically identified common themes pertaining to charcoal's role in deforestation versus forest degradation. Analysis found mixed levels of specificity in the literature implicating charcoal as a driver of the Congo Basin deforestation or degradation, with studies often failing to clarify the mechanisms by which charcoal actors clear or degrade forests, or the extent to which charcoal is directly responsible for deforestation when other drivers are present. Forest impacts in charcoal supply basins surrounding the urban demand loci of Brazzaville, Kinshasa, Kisangani, Goma, Bukavu, Lubumbashi, Bangui, and Yaoundé vary greatly due to heterogenous features of charcoal supply chains, and supply basins vary in growing radii up to 200km from urban centers, even 400km in the case of Kinshasa. Studies calculating the hectares of forest at risk from charcoal also provide mixed estimates based on different computation methods and urban contexts. Future research is needed to clearly delineate the mechanisms by which charcoal, as separate from unprocessed woodfuels, can be implicated in deforestation and degradation of the Congo Basin forests, and modeling the spatial extents of threat to the Congo Basin forests from charcoal will require computation assumptions such as productive capacity of forests of varying compositions for charcoal.

***Figure B1.1** Synthesis of key charcoal-deforestation dynamics findings from the literature relevant for the Congo Basin urban areas that form loci of urban charcoal demand across Central Africa. Blue circles are approximate radius of supply.*


Legend
Forest Fragmentation
Patch forest
Outer edge
Corridor
Inner edge
Intact
Non-forest
Urban Population Estimates, 2020
630000 - 889000
889000 - 1000000
1000000 - 1260000
1260000 - 4200000
1000000 - 14300000
Heatmap: CAFI Drivers of Deforestation Points
Merging Artisanal Agriculture and Artisanal Forestry points (CAFI, 2023)
5,210 total points
Charcoal supply basin rough estimates (see Key Sources)
CAM
CAR
COG
DRC
Bangui
Synthesis
-2020 population estimate ~890,000
-Charcoal supply radius: Median 25km, but wood for supply can originate up to 70km away
-Limited literature on specific forest extents threated by charcoal, some on DRC side
Key sources
(Dubiez et al., 2019)
Kisangani
Synthesis
-2020 population estimate ~1,300,000
-Limited literature on specific forest extents threated by charcoal
-Limited literature disentangling charcoal from other woodfuels
Key sources
(Schure et al., 2011)
Goma
Synthesis
-2020 population estimate ~640,000
-Charcoal supply radius: Up to 100km
-Percent of wood for charcoal sourced from forest: 61%
Key sources
(Gazull et al., 2020, Behrendt et al., 2013, Van Uhm et al., 2022)
Bukavu
Synthesis
-2020 population estimate ~1,100,000
-Charcoal supply radius: Up to 50km including boat and road
-Percent of wood for charcoal sourced from forest: 44%
Key sources
(Imani et al., 2021)
Yaoundé
Synthesis
-2020 population estimate ~4,200,000
-Limited literature on specific forest extents threatened by charcoal but literature pinpoints southeastern and southwest forests
-Approx. 4,000ha "at risk" from charcoal
Key sources
(Defo et al., 2021; Ndah et al., 2024)
Kinshasa/Brazzaville
Kinshasa synthesis
-2020 population estimate ~14,300,000
-Charcoal supply radius: 150-400km
-Percent of wood for charcoal sourced from forest: 51.2%
Brazzaville synthesis
-2020 population estimate ~2,400,000
-Charcoal is primary driver of forest clearing, less common as secondary to agriculture (Boundzanga et al., 2014)
Key sources
Kinshasa: (Dubiez et al., 2021); Brazzaville: (Boundzanga et al., 2014)
Lubumbashi
Synthesis
-2020 population estimate ~2,500,000
-Charcoal supply radius: up to 60km (Kabulu et al., 2018); up to 100km in recent years (Sikuzani et al., 2017)
-Percent of wood for charcoal sourced from forest: Almost entirely from miombo forests (Péroches et al., 2021)
Key sources
(Kabulu et al., 2018; Péroches et al., 2021, Sikuzani et al., 2017; Muteya et al., 2023)

Note: Refer to the disclaimer on page ii for the names and boundaries used in this map.

Source: Bernhard, K.P., Shapiro, A.C., & D'Annunzio, R. 2025. To what extent does charcoal threaten Central Africa's Congo Basin forests? A synthesis of English and French literature. [Manuscript submitted for publication].

Food security and climate change mitigation

In sub-Saharan Africa – more specifically, Central Africa – an overwhelming majority of the predominantly rural communities depend on agricultural and forest-related activities for their basic needs, food and livelihoods, and are associated with forest disturbance (Ickowitz *et al.*, 2015; Mangaza *et al.*, 2021; Pingali, Schneider and Zurek, 2014). A large majority of crops in Central Africa are rainfed, with citizens largely employed in agriculture, making the population particularly vulnerable to the impacts of climate change, which is already reducing yields and slowing the growth of the agricultural sector (Hourticq *et al.*, 2013; Pörtner *et al.*, 2022). Furthermore, with the ongoing crisis in Ukraine and efforts to improve the production of food on the African continent to meet the needs of the population, failing to mainstream climate change (mainly its mitigation component) in the food system may lead to additional deforestation.

The information provided in this study on direct drivers is directly relevant to improving policies and implementing activities that meet the needs of local communities through sustainable development, land use and agricultural planning, which can be supported by international climate mitigation efforts (Branthomme *et al.*, 2023). By identifying the rural complex as the main driver of deforestation in Central Africa, this study highlights the importance of decarbonizing food systems, uncoupling development from deforestation, and the urgency of improving agricultural practices and promoting climate-smart agriculture, which can reduce the carbon footprint of agricultural activities while promoting a resilient and more productive farming system (Mangaza *et al.*, 2021). Other activities include targeting small-scale agriculture activities through rural development initiatives, implemented by local communities. New innovations in agricultural practices need to be implemented to increase productivity, improve livelihoods and reduce pressure to convert forests into agriculture. These innovations include providing new crop varieties which are adapted to local conditions and improve yield, disseminating information on new practices, better post-harvest handling and mechanisms to promote products in local markets, and promotion of agroforestry where possible (Kotto-Same *et al.*, 2000; Sonwa and Hanna, 2017). It is also essential to integrate local context and tailor solutions to properly respond to climate-related risks, outcomes and adaptation, as well as integrate the roles of policy contexts, cultures to inform adaptation policies, strategies and measures (Sonwa *et al.*, 2016).

While we demonstrate that small-scale agriculture is widely driving forest disturbance, appropriate mitigations can only be successful in limiting forest loss if they provide crucial food and economic security. Household farming is fundamental to food systems in sub-Saharan Africa (FAO, 2022b) and plays an important role in achieving Sustainable Development Goal 1: No Poverty and Sustainable Development Goal 2: Zero Hunger, which aren't without inherent challenges (Saxena *et al.*, 2021). While across the globe, agricultural productivity has increased, improvements in yield have been relatively stagnant in African countries. This is further exacerbated in areas where communities are particularly poor, there is population growth further straining available resources, access to agricultural technologies are limited, and the effects of climate change are already having impacts. Specific solutions need to address the weaknesses of these systems that make them inefficient and relatively unproductive, deplete soil resources or require more land.

The improvement of agricultural productivity is often targeted as a strategy to fight global hunger, while also contributing significantly to poverty alleviation (Pingali, 2010). There are several pathways to support agricultural intensification and improvements in efficiency that incentivize approaches that are more sustainable in the long term. From a policy perspective, property rights and land tenure are essential, as farmers are more likely to effectively use land in the long term that they have secure rights to (Pingali, 2001). Intensification should also be targeted in tandem with improvement in market access providing new opportunities for substantial returns, while safeguarding the needs of local communities in the process of adaptation to climate change (Nkem *et al.*, 2010). Technological improvements, as well as research and development efforts, also need to target the crops that are most important to local communities, such as millet and sorghum (Pingali, Schneider and Zurek, 2014). New developments in seed technology can provide new seed varieties that may be more resilient to climate change or pests, which could increase yield and decrease pressure on forests. However, in some studies in the Democratic Republic of the Congo, the introduction of new seed varieties caused a shift in land use from secondary to primary forests as a result of soil nutrient properties (Bernard *et al.*, 2023).

If agricultural activities are increasingly intensified and sedentary, focused around inhabited areas and secondary or degraded forests as shown in this research, what is the role of forests in further agricultural development? It is estimated that more than 1.6 billion people live within close proximity and are potentially dependent on forests for their livelihoods, health and important resources, such as bushmeat or cooking fuel (Newton *et al.*, 2020). Furthermore, non-timber forest products play a crucial role as a safety net providing alternative sources of income and food, in particular during times of need or agricultural failure (Belcher, 2005). However, the demand of particular non-timber forest products (NTFPs), such as charcoal, can fluctuate greatly, and surges from large cities can affect the availability of resources for local communities, in addition to the effects of climate change, land degradation and pressures of population growth (Nkem *et al.*, 2010). Therefore, a diversity of stable, diverse natural resources – most importantly well conserved and productive forests – can help communities across the region adapt and mitigate to changing pressures and climate. Thus, intact forests are a necessity for healthy people and resilient communities.

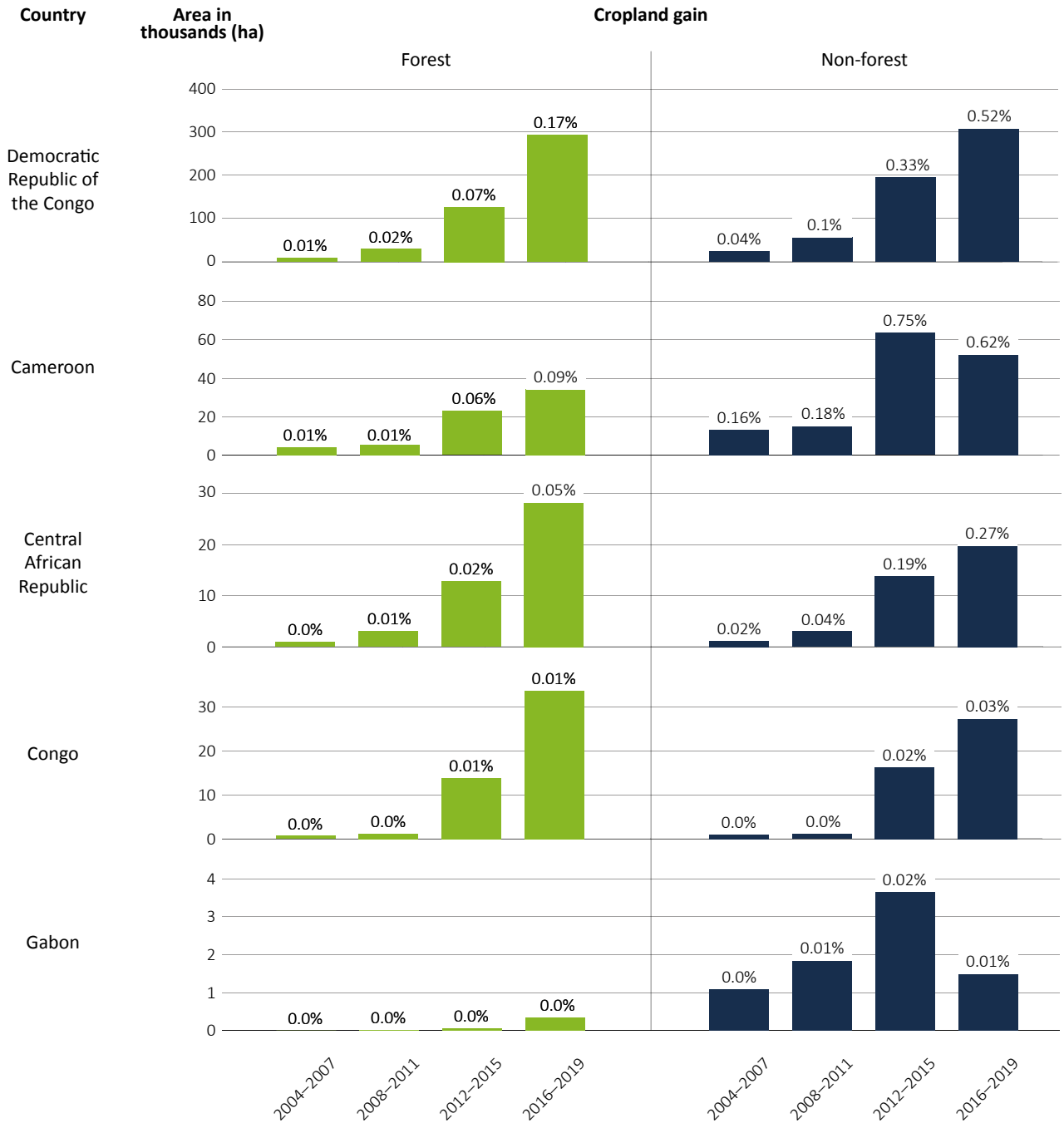
Agricultural activities outside of the forest domain

How can we reconcile increases in population and an associated demand for resources, climate change and political instability with declining deforestation? The answer could lie in areas outside the forest.

It is shown here that deforestation and degradation are primarily occurring in fragmented, accessible forests. Furthermore, the major driver of change is small-scale agricultural activities, which are mostly non-mechanized and for local consumption. This is further confirmed by socioeconomic surveys conducted in pilot landscapes, which also show that community activities are limited to small areas around their villages.

Global data on cropland extent were used to evaluate gains and losses in and outside of a forest mask created for the year 2000 from global forest change data. Expansions in croplands are greater outside forests in several countries, which could indicate that human activities are indeed remaining around settlements and not contributing to additional forest loss in areas defined as forest in 2015. However, this does not mean that these activities are not causing deforestation, as trends in cropland expansion appear to be significantly increasing. A continental-scale study recently mapped individual tree canopies and found that a significant number of trees fall outside of areas that are defined as forests (Reiner *et al.*, 2023), meaning that cropland expansion could potentially incur emissions and tree cover loss. The areas outside the non-forest domain may include regenerating or secondary forests, or individual trees in mixed landscapes that do not meet the national forest definition, or other non-forest vegetated ecosystems (shrublands). This indicates that changes may be occurring and increasing, but simply not in areas defined as forests.

Figure 30. Cropland expansion in the six countries of the study region



Note: Shown as total area with labels indicating percentage of forest or non-forest area. In all countries, expansion is increasing over time; however, in Cameroon, the Democratic Republic of the Congo and Gabon, the total increases are greater outside the forest domain in later time periods.

Source: Potapov, P., Turubanova, S., Hansen, M.C., Tyukavina, A., Zalles, V., Khan, A., Song, X.-P. *et al.* 2022. Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. *Nature Food*, 3(1): 19–28. https://doi.org/10.1038/s43016-021-00429-z

Expansion and decrease are greater outside of the forest domain in Cameroon, Democratic Republic of the Congo and Gabon. In the Central African Republic, the area of cropland expansion is greater inside the forest domain in the last time period, but the probability of conversion is far greater in non-forest. The cropland expansions in countries such as Cameroon and Democratic Republic of the Congo, even if outside forests, still represent significant area and could be a continued threat to emission reductions in the long term if they continue to move into forested areas.

Forest governance and climate change mitigation

Agricultural activities contribute significantly to the gross domestic product of the countries of interest, and much needed economic development often comes with the risk of losing more forests. Therefore, climate change adaptation should be mainstreamed into national planning mechanisms and development should be uncoupled from deforestation, where possible. The information provided here on direct drivers is directly relevant to improving policies that meet the needs of local communities through sustainable development, land use and agricultural planning, supported by climate mitigation efforts.

These findings are important for the implementation of REDD+ and other climate change mitigation and adaptation activities in Central Africa. During the Twenty-sixth Conference of the Parties (COP26) in Glasgow, international commitments of investing USD 1.5 billion into Central Africa were made. While early studies identified logging and agriculture-related activities to adapt to climate change in Central Africa, successive research has noted difficulties in transforming REDD+ frameworks into realities (Bele, Sonwa and Tiani, 2015; Mangaza *et al.*, 2021; Sonwa *et al.*, 2010), and that countries are unable to fulfil their commitments to meeting climate change mitigation targets.

In order for public and private investments to be successful, they need to be focused on targeting relevant direct and indirect drivers of deforestation and be supported by monitoring mechanisms that could measure and validate impact. International efforts aimed at reducing the pressure of agricultural supply chains on forests (deforestation-free supply chains) may in fact have very limited effects in the context of our study area, where artisanal agriculture is the main driver of deforestation and forest degradation, and poorly connected to global markets. This research can provide a better understanding of current forest loss, degradation, rates of disturbance and the dynamics and interactions of direct drivers on carbon stocks to prioritize and locate specific, effective interventions. This can help prompt early action to mitigate carbon emissions and inform relevant land-use policies to respond directly to relevant drivers and specific activities, such as improving agricultural practices and their resilience, supporting land-use planning to foster ecosystem connectivity and intensify agricultural use, target illegal activities such as small-scale mining, or promote better practices in industrial exploitation. The current study also supports crucial institutional capacity development of partner nations to derive information that will be useful in monitoring, reporting and verification efforts, through transparent methods and approaches, while providing specific information to focus mitigation activities and respond to specific drivers of change and define development pathways to avoid further climate degradation.

Although deforestation and degradation rates are typically low in the Central African region, the potential environmental and socioeconomic impacts from continued uncontrolled exploitation and conversion have been recognized by national governments. As a result, efforts to manage forest resources through sustainable management initiatives, international cooperative efforts, and agreements have been implemented. Some examples of the cooperation of Central African member states through international and regional initiatives, backed by significant investments to provide harmonized, strategic policies and cooperation for better forest management, include: the Central African Forest Commission (COMIFAC); the Congo Basin Forest Partnership (CBFP), the UN-REDD programme aiming to reduce emissions from deforestation and degradation; and CAFI's results-based payment agreements and various bilateral initiatives. New international climate financing mechanisms, such as the public–private Lowering Emissions by Accelerating Forest finance (LEAF) Coalition and bilateral agreements, are generating further incentives and momentum to implement deforestation reduction programmes, which should be used to address the major obstacles to effective forest management, including: the need for increased involvement and inclusion of local populations within land management and decisions; the implementation of successful community forestry initiatives; the clarification of local land tenure, rights and ownership of forest resources; the development of technical capacity within national institutions; and the need for better forest monitoring and carbon accounting (Djomo *et al.*, 2017). With robust, reliable data and outputs, the proposed approach provides a straightforward pathway to understand better status and trends of deforestation and degradation drivers. Only through the provision of this type of information on drivers and trends can existing pilot efforts be sustained and further developed to have a wider, longer-term impact on poverty and food security.

Conclusions

A globally replicable and transferrable approach has been developed to determine the relative contribution of direct drivers to deforestation and degradation. This method has been piloted in six countries of Central Africa, to address the scale and impact of small-scale agriculture as the major driver of forest change, occurring primarily in secondary and fragmented forests. This information can be used to target mitigations to improve agricultural productivity and efficiency to reduce the need to clear more land are essential to conserving forest ecosystems and enhancing resilience and adaptation to climate change. International initiatives to reduce demand on agricultural commodities, while very important for key commodities, will unfortunately have limited effects in the region, which is not as well connected to global markets.

This research provides a better understanding of the drivers of recent forest loss, degradation, and the dynamics and interactions of direct drivers on carbon stocks, in order to help countries fulfil their commitments to meeting climate change mitigation targets. We show that low-impact drivers, such as artisanal agriculture and forestry associated with the rural complex, are primarily driving deforestation and degradation, while industrial drivers with more significant impacts are spatially limited. This research indicates that more resources need to be invested towards sustainable, climate-smart agriculture to meet the needs of local populations, while conserving forest resources.

The approach presented here is the first to address a wide variety of unique and overlapping drivers in the spatial and temporal dimension, executed through a collaborative international partnership. This is useful to support crucial institutional capacity development of partner nations to derive information that is for mitigation activities, responding to specific drivers of change, and defining development pathways to avoid further climate degradation. The methodology is adaptable and can be updated for new time periods, uses, and open-source tools, encouraging replication and uptake. This aspect is important, as a five-year time period is likely too short to realistically observe post-disturbance dynamics, the establishment of new land uses, and the potential impacts of recent investments and initiatives. Therefore, an update incorporating a longer study period is needed to validate these assessments. Over a longer time span, we could validate these observed trends and potentially observe forest regrowth or regeneration, which is not yet considered here. In addition, the evaluation of potential impacts on biodiversity and standing carbon stocks are important to determine relative emissions and will complement this effort to focus conservation activities and guide land-use planning efforts.

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